Jarkko Tulensalo

Utilization of a Power Market Simulator in Power Adequacy Assessment

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Thesis supervisor:

Prof. Matti Lehtonen

Thesis advisor:

M.Sc (Tech.) Risto Kuusi

Aalto-yliopisto

AALTO UNIVERSITY
SCHOOL OF ELECTRICAL ENGINEERING

ABSTRACT OF THE
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Author: Jarkko Tulensalo

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Supervisor: Prof. Matti Lehtonen

Advisor: M.Sc. (Tech.) Risto Kuusi

Finland is dependent on the electricity import capacity of the neighboring countries during peak demand hours. In addition, a significant amount of condensing power has been dismantled within the Baltic Sea market area during the recent years. The changes raise a question if the current power system is capable to cover the need for electricity at all times both now and in the future.

This thesis proposes a probabilistic power adequacy analysis method for the assessment of the Baltic Sea market area based on the use of a power market simulator and Monte Carlo simulation. The method takes stochastically wind power, hydro inflows, demand, CHP and outages of both power plants and interconnectors during each hour of the year into account. As a part of this thesis, a stochastic outage generation tool was introduced which models outages according to a lognormal distribution function.

In the thesis, the applicability of the proposed method was evaluated by assessing the power adequacy of Finland with two case studies which showed that the method produces sensible results. According to the results, the power adequacy of Finland decreases during the years 2012–2023 resulting from decreasing thermal capacity of Finland and its neighboring countries. The second study showed that 800 MW reinforcement on the interconnector capacity between North Sweden and Finland would significantly improve the power adequacy level of Finland. This thesis concludes that the method can be used as a tool for long-term power system adequacy analysis in various applications.

Keywords: Adequacy, Power Market Simulator, Monte Carlo Simulation, Stochastic Fault Modeling, Baltic Sea Electricity Markets

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Suomi ei ole teho-omavarainen huippukulutustunteina, jolloin se tarvitsee tuontisähköä naapurimaista. Sen lisäksi Itämeren alueen sähköjärjestelmästä on poistunut huomattavasti lauhdekapasiteettia viime vuosina. Suuret muutokset sähköjärjestelmässä herättävät kysymyksen, riittääkö sähköä kattamaan kulutusta jokaisena vuoden tuntina nyt ja tulevaisuudessa.

Tässä diplomityössä kehitettiin todennäköisyyspohjainen menetelmä Itämeren alueen sähkötehon riittävyyden analysoimiseksi. Menetelmä perustuu sähkömarkkinamallin käyttöön ja Monte Carlo -simulaatioon, joka käsittelee stokastisesti tuulivoimaa, vesivoimaa, kulutusta, kaukolämmön sähköntuotantoa sekä voimalaitosten ja siirtoyhteyksien vikaantumisia jokaisena vuoden tuntina. Työssä luotiin myös uusi työkalu, joka mallintaa vikaantumisia logaritmisen todennäköisyysjakauman avulla.

Työssä arvioitiin menetelmän soveltuvuutta Itämeren alueen sähkömarkkinoiden analysointiin kahdella eri sovellutuksella, joiden tuloksien mukaan menetelmä toimii järkevästi. Tuloksien mukaan Suomen sähkötehon riittävyys heikkenee tarkastellun ajanjakson aikana 2012–2023 lämpövoimakapasiteetin supistuessa. Toisen sovellutuksen mukaan Suomen ja Ruotsin välisen rajasiirtokapasiteetin nostaminen 800 MW:lla parantaisi Suomen sähkötehon riittävyyttä huomattavasti. Työn yhteenvedossa todetaan, että menetelmä soveltuu työkaluksi voimajärjestelmän pitkän tähtäimen suunnittelussa.

Avainsanat: Sähkötehon riittävyys, sähkömarkkinamallinnus, Monte Carlo -simulointi, vikaantumisten stokastinen mallintaminen, Itämeren alueen sähkömarkkinat

Preface

This thesis was written in the transmission system operator Fingrid Oyj as a master's thesis for the Department of Electrical Engineering, Aalto University. During the writing of this thesis, I have received help and support from a lot of people who I want to thank.

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Contents

Abstract **ii**

Preface **iv**

Contents **v**

Nomenclature **vii**

1 Introduction 1

1.1 Background of the Thesis 1

1.2 Objective of the Thesis 2

1.3 Scope of the Thesis 2

1.4 Structure of the Thesis 3

2 Power Adequacy Analysis 5

2.1 Adequacy Definition 5

2.2 Adequacy Indices 8

2.3 Adequacy Criteria 9

2.4 Adequacy Analysis Methods 10

2.5 Study of Previous Adequacy Analysis Reports 13

2.5.1 Methodology 13

2.5.2 Modeling of Input Parameters 15

2.5.3 Main Findings 17

3 Characteristics of the Baltic Sea Electricity Market 18

3.1 Power Capacity 18

3.2 Electricity Demand 21

3.3 Transmission Lines between Finland and its Neighbors 23

4 Power Market Simulator 26

4.1 General 26

4.2 Samkjøringsmodell 26

4.3 BID 27

5 Power Adequacy Analysis by a Power Market Simulator 28

5.1 The Monte Carlo Simulation Method 28

5.2 Stochastic Modeling of Outages 29

5.2.1 Introduction 29

5.2.2 Input Parameters 30

5.2.3 Functionality 31

5.3 Weather Dependent Parameters ... 36
5.4 Proposed Power Adequacy Analysis Method ... 40
5.4.1 Methodology ... 40
5.4.2 Input Data ... 41
5.4.3 Output ... 43
6 Simulation Cases Applied to the Baltic Sea Market Area ... 46
6.1 Geographical perimeter of the Simulation Cases ... 46
6.2 Sensitivity Analysis on Simulation Parameters ... 47
6.2.1 Simulation Program Run Settings ... 47
6.2.2 Convergence of the Results of the Power Market Simulator ... 49
6.3 Application to the Baltic Sea Market Area ... 50
6.3.1 Case Study 2012–2023 ... 50
6.3.2 Case Study - Interconnector Analysis ... 51
7 Results of the Simulation Cases ... 52
7.1 Sensitivity analysis on the Simulation Parameters ... 52
7.1.1 Simulation Program Run Settings ... 52
7.1.2 Convergence of the Results of the Power Market Simulator ... 56
7.2 Application to the Baltic Sea Market Area ... 59
7.2.1 Case Study 2012–2023 ... 59
7.2.2 Case Study - Interconnector Analysis ... 63
7.3 Reliability Analysis on the Results ... 66
8 Discussion and Conclusions ... 68
8.1 Observations about the Proposed Method ... 68
8.2 Sensitivity Analysis on the Simulation Parameters ... 69
8.3 Applicability of the Method in the Case Studies ... 70
9 References ... 72
10 Appendices ... 77
Appendix A Algorithm for the Generation of the Duration of the Outage ... 77

Nomenclature

Symbols

E(x)	Mean of the lognormal distribution
n	Number of model runs
n_{fault}	Average number of faults occurring during a year
p_{occ}	Probability of a fault occurring
$SD(x)$	Standard deviation of the lognormal distribution
$z_{\alpha/2}$	Confidence level
w	Confidence interval width
μ	Log-normal distribution mean parameter
σ	Log-normal distribution variance parameter

Abbreviations

AEMO	Australian Energy Market Operator
CHP	Combined Heat and Power
DSR	Demand Side Response
EAAP	Energy Adequacy Assessment Projection
ELCC	Effective Load Carrying Capacity
EMPS	EFIs Multi-area Power Scheduling Model
ENS	Energy Not Served
ENTSO-E	European Network of Transmission System Operators for Electricity
HVDC	High Voltage Direct Current
LOLP	Loss of Load Probability
LOLE	Loss of Load Expectancy
NERC	North American Electric Reliability Corporation
PINT	Put IN one at the Time
PLEF	Pentalateral Energy Forum
SOAF	Scenario Outlook & Adequacy Forecast
TSO	Transmission System Operator
VoLL	Value of Loss Load

1 Introduction

1.1 Background of the Thesis

The electricity generation capacity is not adequate at the moment to cover the demand in Finland during peak demand hours, when it is dependent on the import capacity of the neighboring countries (Pöyry 2015). The current power system is facing many changes, as intermittent wind and solar power is expected to replace conventional power plants. During the years 2013–2015, over 2000 MW of condensing power was dismantled in Finland (Nord Pool Spot 2015b). The massive changes raise a question if the current power system is capable to cover the need for electricity at all times both now and in the future.

The probability of electricity running out in a power system can be assessed with power adequacy analysis. Elovaara & Haarla (2011) define the adequacy as the ability of a power system to provide enough power and energy to cover the need for electricity demand during all times when planned and unplanned outages are taken into account.

Over the past few years, the research has attempted to explore the stochastic issues in power adequacy while the majority of the recent reports by different transmission system operators have focused on the framework. Even though stochastic methods were already studied in the 1960's (Garver 1966), the lack of computing power lead to the use of deterministic methods until the recent years. Now, the trend has been slowly moving towards probabilistic methods again with the development of computer technology. The stochastic methods have already been proved to be essential when conducting adequacy analysis. However, there is no comprehensive reference for a stochastic method, which could be directly implemented for the analysis of the Baltic Sea power systems. Different power systems have special characteristics that need to be taken into account, which is why the existing methodologies cannot be directly implemented as such for the analysis of the Baltic Sea power systems.

This thesis provides a comprehensive state-of-the-art method for the assessment of the power adequacy of a power system with stochastical characteristics. The method was especially developed for the Baltic Sea power system, but can also be applied for the analysis of other power systems. The method takes stochastically the changing weather conditions and unplanned outages in the power system during each hour of the year into account. This allows the analysis of the power system during millions of different situations. The weather conditions occur according to historical data series and outages with their appropriate statistical probability. A stochastic tool was introduced in this thesis in order to model faults in the power system stochastically and in detail. The introduced representation of the faults is a significant improvement to the approximate representations that have previously been used.

1.2 Objective of the Thesis

The objective of this thesis is to develop a power adequacy analysis method utilizing a power market simulator for the assessment of the Baltic Sea market area and to assess its applicability. The model should be able to take stochastic characteristics of a power system into account and to produce sensible results within the limits of the input data. The model can be used as a tool for long-term power system planning concerning future grid investments.

1.3 Scope of the Thesis

The reliability of a power system can be divided into two parts: adequacy and security of supply. Adequacy describes the ability of a power system to supply enough power and energy to match the needs of the demand taking planned and unplanned outages into account. Security of supply depicts the capability of a power system to withstand sudden disturbances. (Elovaara & Haarla 2011, p. 276–277) This study focuses on adequacy.

Power adequacy analysis assesses the probability of an occurring load loss resulting from curtailment. In this thesis, curtailment is defined to take place when the net demand exceeds the sum of available generation and available transmission import capacity at the day-ahead market. This means that market mechanism working after the day-ahead market are not taken into account, which is align with the focus on adequacy. Market place for physical electricity transactions in the next day is called day-ahead market (Fingrid Oyj 2016a).

The choice to limit the study to day-ahead markets has an influence on two things. Firstly, all market players are assumed to offer all of their available capacity to the day-ahead markets. In reality, market players can offer their capacity to different markets. Secondly, the scope limits the interpretation of the results to purely the day-ahead markets. Curtailment at the day-ahead market does not necessarily mean that electricity runs out or power needs to be reduced from the customers. It means that the day-ahead market solution could not be established. How the situation would be resolved during the intraday, is not discussed in this thesis.

Comparison of different power market simulators and the assumption on the modeling input data are set as out of the scope of this study. The results are simulated with the power market simulator BID

3.1.3. It is tested how well the results of the study correspond to the modeled input data in the study. The results should be interpret as the adequacy level according to the underlying assumptions and input data. However, this thesis does not take a stand if the assumptions are correct or not. Consequently, sensitivity analyses on the modeling assumptions are not performed. Value of loss load (VoLL) calculations are not discussed in this thesis.

Demand, hydro power, wind power and combined heat and power related to district heating are assumed as weather dependent factors which are interdependent. Demand is used in this study as a synonym for electricity demand. The interdependency means that the weather dependent factors are based on historical temperature, precipitation and wind data. The weather dependent factors are considered as independent with the power plant and the interconnector outages.

1.4 Structure of the Thesis

Chapter 2 introduces the main concepts of the field of study and mostly used adequacy indices. The acceptable level of adequacy of different European countries is also discussed. Previous adequacy analysis methods from different studies over the world are presented and compared with each other's.

Chapter 3 explains the main characteristics of the current Baltic Sea electricity market as well as the main future trends. The chapter focuses on the relevant characteristics especially affecting the generation adequacy of the Finnish power system. The aspects cover power capacity, demand and interconnectors.

Chapter 4 examines the general properties of power market simulators. Two examples of power market simulators are presented, one of which is used for the simulation of the case studies in this thesis.

Chapter 5 introduces the proposed adequacy analysis method and the underlining assumptions used. First, the basics of the Monte Carlo method are explained. Second, the modeling of stochastic parameters is discussed. In the chapter, a new method is introduced about the stochastic modeling of unplanned outages of units.

Chapter 6 describes the simulation case studies that were performed in this thesis and Chapter 7 presents their results. At first, two sensitivity analyses on the simulation parameters are explained. Then, two applications of the proposed method are presented.

Chapter 8 discusses the main observations and findings about the method, sensitivity analyses and the case studies.

2 Power Adequacy Analysis

This chapter establishes a base for the main concepts related to adequacy and adequacy analysis methods. First, the mostly used concepts and indices of the field of study are defined. Then, the allowed adequacy level of a power system in different countries is discussed. Finally, a closer look on the previous knowledge in the field of area is taken and their findings related to this thesis are presented.

2.1 Adequacy Definition

Traditionally, the term generation adequacy has been associated with sufficient generation capacity to meet the peak demand. There have been doubts if the traditional way of thinking is sufficient with the introduction of intermittent renewable energy sources and flexible demand to the power system. The change in mindset is enforced by using the term power adequacy in this study. Power adequacy should cover both the capacity and the energy perspective.

If power supplied is not enough to meet the demand, curtailment or power outage occurs. Doorman et al. (2004, p. 13) defined curtailment as 'necessary when either there is a physical shortage of energy or capacity that is not solved by high prices'.

The report (Doorman et al., 2004, p. 15–18) differentiated a shortage of energy from a shortage of capacity as being a question of long and short term problems. A shortage of energy is a long term problem caused by scarcity of primary energy, long term outages of major power plants or unavailability of major interconnections. For example, a low yearly precipitation can cause a shortage of energy in a market where a significant part of the generation capacity is hydropower, such as the Nordic Power market. The Nordic power market comprises Finland, Sweden, Norway and Denmark.

The report (Doorman et al., 2004, p. 15–18) defined a capacity shortage as the power system's inability to cover instantaneous demand, which is caused by the lack of available generation or transmission capacity. A capacity shortage was considered as a short term problem, which can last for only a few hours during a day. For power adequacy studies, both the energy and the capacity shortage should be taken into account.

A blackout refers to a situation where electricity is interrupted for a long period of time from a wide geographical area and a consequence of a series of unwanted events (Doorman et al. 2004, p. 15–18), but this perspective is not covered in this study. The day-ahead market is only taken into consideration, which is why power curtailment is defined as follows in this study:

Curtailment takes place when the demand exceeds the sum of available generation and transmission import capability at the day-ahead market.

Power adequacy can be presented in terms of available generation capacity, available transmission import capacity and demand as shown in Figure 1. Curtailment would occur if the demand column on the right surpasses the available capacity column in the middle. The available capacity includes available generation capacity and available transmission capacity. Available transmission capacity may improve the power adequacy level depending on the capacity situation in the neighboring countries as well as the generation capacity inside the country.

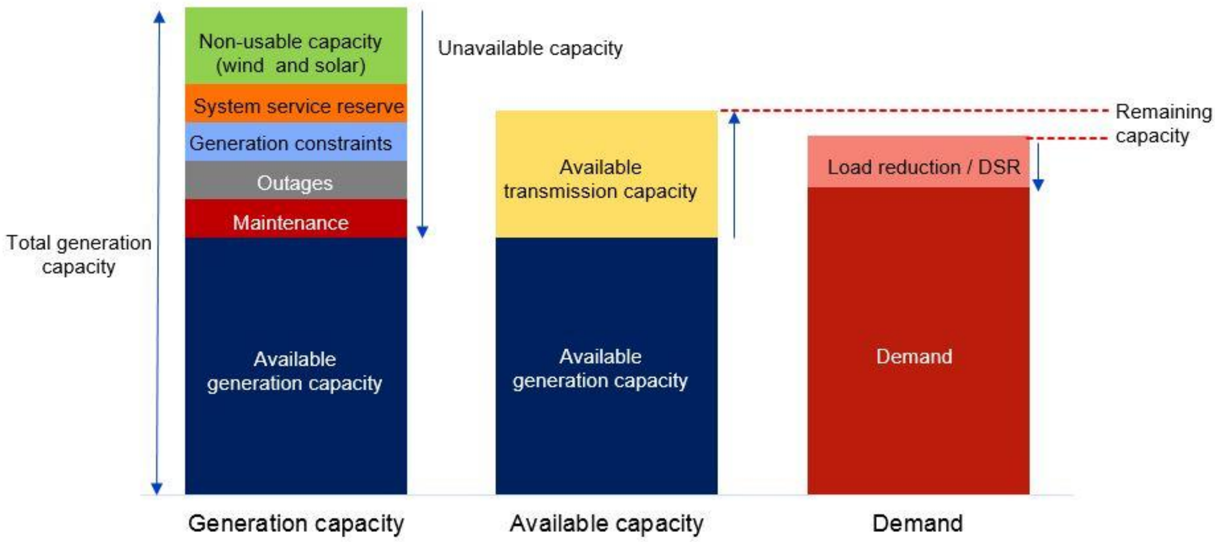

Figure 1: *The composition of power adequacy modified after (ENTSO-E 2015c).*

The capacity that cannot be used to generate power at point of time for any reason is referred to as unavailable capacity. The categorization of available and unavailable capacities might be defined differently in various studies depending on the purpose and the methodology of the research. In this study, they are defined as shown in the left hand column in Figure 1.

The unavailable capacity includes generation capacity under maintenance, outages, generation constraints, system service reserve and non-usable capacity (ENTSO-E 2015c, p. 9). Maintenances are typically scheduled during off-peak demand periods. However, it is always possible that a generator could fail unexpectedly at any time of the year. This unexpected nature of forced outages is a primary concern of reliability analysis. (Holttinen et al. 2009, p. 131) Generation constraints are situations where generation capacity is limited because of shortage of energy, for example the previously mentioned situation of low yearly precipitation.

Non-usable capacity mostly consists of renewable generation capacity, such as wind and solar power, which are not always available at their rated power due to changing weather conditions. (ENTSO-E 2015c, p. 9) Non-usable capacity can also consist of combined heat and power (CHP) capacity which is not able to produce electricity at rated power at all times. The amount of available electricity generation capacity can correlate with the heat production of the power plant, therefore during periods of lower heat demand, the production capacity of electricity may decrease. This means that the non-usable capacity of the CHP plants increases.

The Nordic Grid Code (Nordel 2007) states that each country must also procure system service reserves, which are needed for frequency control and handling situations after disturbances. The system service reserves consist of normal operation and disturbance reserves. Their purpose is to control frequency and to serve as a backup in the case of a large generation unit failure. These reserves are maintained at all times and are not available at the day-ahead market. (Fingrid Oyj 2016d) The system service reserve capacity is categorized as unavailable since it is a market mechanism working after the day-ahead markets.

The strategic reserve is not included in the system service reserve. They are offered to the day-ahead markets, which is why they are included in the available generation capacity in this study. Strategic reserve is also known as peak load capacity in some countries. The peak load capacity secures the security of electricity in situations where the planned electricity production is not sufficient to cover the estimated electricity consumption (Fingrid Oyj 2016c).

Demand side response (DSR) is shown in Figure 1 on the top of the right handed column as a component that can decrease the total demand. Demand side response means electricity consumers which can decrease the consumption of electricity momentarily (VTT 2014). It can occur naturally when high electricity prices at the electricity wholesale market result in a decreased demanded quantity of electricity. Elovaara & Haarla (2011, p. 50) highlighted the need to extend the demand side response to smaller electricity customers. There is a lot of research going on how to change the demand pattern of end customers and small industry, when high electricity prices occur at the electricity wholesale market (Fingrid Oyj 2016b). DSR is covered more in Section 3.2.

2.2 Adequacy Indices

Power adequacy can be analyzed with different indices. They can be applied to set a certain target limit for the power system and as a reference for system planning. Indices also allow the comparison of different power systems. (Elovaara & Haarla 2011) In addition to Elovaara & Haarla (2011, p. 424–425), Billington et al. (2013, p. 109–111) and North American Electric Reliability Corporation (NERC) (2011, p. 9–13) defined reliability indices which are used in adequacy analysis (Table 1).

Table 1: *Reliability indices used in adequacy analysis*

Abbreviation	Description	Unit
ENS	Energy Not Served	MWh/year
LOLP	Loss of Load Probability	–
LOLE	Loss of Load Expectancy	h/year
Remaining Capacity	Remaining Capacity	MW
ELCC	Effective Load Carrying Capacity	MW

Energy Not Served (ENS) indicates the estimated energy which would have been supplied to end users if no interruption and no transmission restrictions had occurred (The Energy Concern’s National League 2001, Nordel 2008, p. 16). ENS can be calculated by multiplying the power before the fault and the outage duration. The unit for ENS is MWh/year. (Nordel 2008, p. 53) This thesis only studies ENS resulting from curtailment.

Loss of Load Probability (LOLP) index describes the probability of curtailment. LOLP can be calculated for each hour of the year indicating the probability of curtailment occurring in a specific hour of the year. LOLP is often illustrated with a distribution profile (Billinton et al. 2013). Loss of Load Expectation (LOLE) is calculated by summing up the LOLP values over time of reference, for example a day or a year. LOLE can be interpreted as the total expected time when load must be reduced or cut. (Elovaara & Haarla 2011, p. 424) North American Electric Reliability Corporation (2011, p. 10) explained the general principle of how to calculate LOLE values in its study:

> Non-zero LOLE values occur during peak periods and near-peak periods, and possibly during times that large amounts of capacity are undergoing scheduled maintenance and is therefore unable to provide capacity. The LOLE calculation effectively looks for hours or days

when there is some risk of not meeting load, discarding the vast majority of days or hours during which there is little to no risk (LOLE≈= 0).

The contribution of individual generators to Power Adequacy can be analyzed with a parameter called Effective Load Carrying Capacity (ELCC). There are different methods of calculating the ELCC of a specific generator and the method differs according to the scope of the study and the type of the resource. North American Electric Reliability Corporation (2011) explains a method in their study where the contribution of a conventional generator is a function of the unit's capacity and the forced outage rate. The contribution of a variable generation can be estimated with the resource's capacity factor over a time period that corresponds to system peak demand hours. These approaches provide a simplistic approximation of system adequacy. However, North American Electric Reliability Corporation (2011, p. 2) and Matilainen et al. (2009) both point out in their studies that the characteristics of the power system can affect the approximated ELCC value depending on the method of calculation.

Previous studies (Elovaara & Haarla 2011, p. 424; Pentalateral Energy Forum 2015, p. 18–19) have argued that LOLP and LOLE indices are not meaningful to some power systems with the very low risk of a power deficit. Therefore, other power adequacy indices have also been developed. Pentalateral Energy Forum (PLEF) used a parameter called Remaining Capacity (Figure 1) to describe how much demand could be increased, until curtailment occurs. PLEF is a temporary intergovernmental initiative on the cross-border exchange of electricity in the region of Central European countries. The Remaining Capacity parameter allows the analysis and the comparison of different systems, even though, the risk of a power deficit is very low. (Pentalateral Energy Forum 2015, p. 18–19) Other studies have also used similar parameters, but with the different names. For example, Matilainen et al. (2009) applied the Margin to failure parameter for the assessment of the Finnish power system.

2.3 Adequacy Criteria

The adequacy indices of different power systems cannot be ambiguously compared, which makes it difficult to set an allowed limit. There has not been established a standardized, allowed adequacy limit for power systems, even though some of the reliability indices have been standardized (Elovaara & Haarla 2011, p. 427). The closest to criteria is an EU directive which states that Member States must take necessary measures to secure high security of supply (2005/89/EC Article 5(1b). The directive, thereby shifts the supervision of power system adequacy to each of its Member States. (Nordic Energy Regulators 2009)

There are different approaches how the member countries have implemented the directive. Some countries have legislation that defines the allowed adequacy limit. Belgium, France and Great Britain have implemented a loss-of-load-expectancy limit of 3 h/year, whereas, Netherlands and Ireland have set the limit to 4 h/year and 8 h/year respectively (Pentalateral Energy Forum 2015, THEMA Consulting Group 2015). The traditional target has been 0.1 days/year in the USA, which stands with 2.4 h/year (NERC 2011). Australian Reliability Standard requires that a maximum of 0.002 % of all operational consumption is allowed to go unserved for any region in any financial year (AEMO 2014).

Finland and Sweden have legislation that empowers the regulator in Finland and the transmission system operator in Sweden to procure enough peak load capacity to account for adequacy problems. The peak load capacity is used to account for situations when power supplied is not enough to cover the demand. (Nordic Energy Regulators 2009) The peak load capacities are 299 MW (Energiavirasto 2015) and 1000 MW (Nord Pool Spot 2015b) for Finland and Sweden respectively for the two-year period starting from the winter 2015.

The Finnish peak load capacity act (117/2011) states that it is the duty of the Finnish Energy Authority to define the size of the required peak load capacity at least every four years. Also, the amount of the peak load capacity should be sized so that it improves the maintenance of a good security of supply during peak demands and disturbances in importing capability. The peak load capacity law indicates that the Finnish Energy Authority sets the allowed adequacy criteria in Finland by determining the needed capacity. The more peak load capacity there is in the system, the more adequate the system is. On the other hand, more peak load capacity means increased costs.

2.4 Adequacy Analysis Methods

Deterministic and stochastic modeling

Adequacy assessment methods can be roughly divided into two main categories by the calculation method. The first is a deterministic approach and the second is based on a stochastic analysis.

Characteristic of deterministic modeling are single-point estimates and scenario analysis (North Carolina State University 2013). Single-point estimate means that each uncertain initial value is assigned an appropriate estimate. There can be different discrete scenarios to highlight the uncertainties in the estimation. The commonly used method is to create scenarios for the best case, the worst case and the most likely case, in which all the initial values can be changed according to the scenario. (Palisade

2015) Another deterministic method, the capacity margin method, sums up the contribution of each individual generator to generation adequacy and compares it against the peak demand.

Probabilistic, also known as stochastic modeling assigns uncertain parameters a range of possible values to simulate hundreds or thousands of possible outcomes. The results can be analyzed to get the probability of each outcome occurring, also referred as probability distribution. Distribution can be interpret as what can happen and how likely it is. (Palisade 2015)

The advantages of deterministic over stochastic modeling are smaller calculation time and easier data handling. It can be difficult to assign appropriate values to parameters that have a wide range of possible outcomes. Assigning properly would presume that large amounts of historical data are available. The scenario way of thinking simplifies the problem, and only a couple of distinguish states are needed. Also, scenario modeling produces only as many different results as there are scenarios. The smaller number of results makes it easier to analyze and make conclusions. (Palisade 2015)

However, the problems in deterministic modeling are related to its simplifications. The outcome of the result correlates highly with the assigned parameter values (North Carolina State University 2013). Therefore, the results are highly dependent on the quality of the assigned parameters. The scenario way of thinking calculates the outcome of a couple of possible cases, as stochastic analysis can analyze hundreds or thousands of different possibilities. The stochastic modeling allows the monitoring of how probable the outcome is, which is not possible with the deterministic approach. The deterministic method treats all the scenario outcomes as they were equally likely, which can be misleading. (Palisade 2015)

According to North American Electric Reliability Corporation (2011) and Milligan et al. (2005), the adequacy analysis in the USA has been focusing on approximation approaches. The approach adds the installed capacity of all the individual generators and applying a planning reserve on top. However, these methods rely on simplifications that were originally derived from probabilistic methods and the modeling of intermittent energy sources is challenging with this approach. (Milligan & Porter 2005. NERC argued that an approximation approach becomes less meaningful with large penetrations of renewable generation. (NERC 2011)

Approximate, frequency distribution and chronological methods

Holttinen et al. (2009, p. 135–139) introduced another way to divide adequacy assessment methods according to the data requirements of the method. This way the methods can be divided into three categories: approximate, frequency distribution and chronological (Figure 2). The approximate method is a deterministic approach, whereas the frequency and the chronological methods are stochastic approaches. This categorization has the advantage of differentiating chronological from non-chronological stochastic methods. It should be noted that, the name frequency distribution method refers to the statistical representation of values. The name should not be associated with frequency related to power quality.

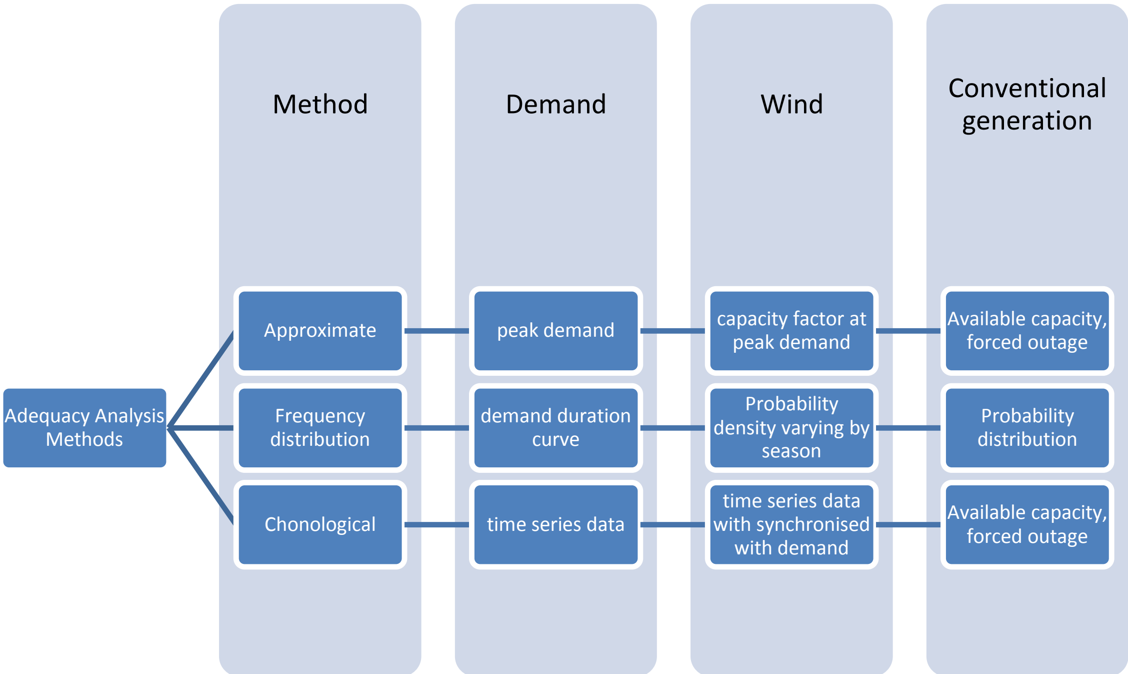

Figure 2: *The data requirements for typical adequacy analysis methods modified after* (Holttinen et al. 2009)

The chronological method has the most extensive input data requirements of the three and it can be used to perform a multiyear adequacy analysis. The approach requires historical wind and demand variation from 10–30 years to be available. Generation adequacy can be assessed from system observation in the time domain using several time series. The chronological approach utilizes synchronized time series data from both demand and wind data, in addition to a complete modelling of the capacity and the forced outage rates of conventional generation units. The model can also include transmission and distribution capacities and constraints. (Holttinen et al. 2009)

Frequency distribution is another probabilistic approach to adequacy assessment which does not need as extensive input data as the chronological method. The frequency distribution method is based on convolving probability distributions of generating units and the demand duration curve. Probability distributions of generating units can be derived from the observed or estimated total forced outage time of the unit. The demand duration curve depicts demand data that is ordered in descending order of magnitude. Wind power probability function can be derived from long-term statistics on wind power availability. (Holttinen et al. 2009)

Holttinen et al. (2009) explained the main reason for the use of the frequency distribution method of being the lack of appropriate chronological data. However, the approach is not as accurate as the chronological approach, since correlation between wind power production and demand variation is difficult to represent without chronological data.

Approximations methods have been developed to ease the calculation and data requirements. The simplified methods are generally based on a capacity factor that is calculated over a predefined peak period. The advantage of the method is that it is easy to understand and therefore transparent. Approximations, however, will not be able to find potential stressful situations when demand is not especially high. Also, the correlation between peak demand hours and wind generation cannot be modeled with the approximation methods. (Holttinen et al. 2009)

2.5 Study of Previous Adequacy Analysis Reports

In this section, previously published adequacy analysis methods are explained and discussed. In addition to European Network of Transmission System Operators for Electricity's (ENTSO-E) method, methods presented by Pentalateral Energy Forum (PLEF), VTT, PJM, The North American Electric Reliability Corporation (NERC) and Australian Energy Market Operator (AEMO) are examined. ENTSO-E is a cooperative body of European Transmission System Operators (Elovaara & Haarla 2011). VTT is the technical research center of Finland. PJM is a regional transmission organization in its area of north-eastern USA (PJM 2015).

2.5.1 Methodology

Most of the power adequacy analysis reports are published by transmission system operators and their co-operative bodies around the world. Previous adequacy analysis reports commonly used approximation methods with a scenario way of thinking. Now, the methodology trend is transitioning towards probabilistic methods which are applied with an hourly resolution. Some previously published studies around the world were selected which are presented below.

ENTSO-E target methodology (2014) and North American Electric Reliability Corporation (2011) presented appropriate adequacy analysis methodology's to be used in today's electricity market in Europe and USA respectively. ENTSO-E also published a study called 2015 Scenario Outlook & adequacy Forecast (SOAF) (2015b) which analyzed the European power adequacy. In addition, Pentalateral Energy Forum (2015), VTT (2014), PJM (2003) and Australian Energy Market Operator (2013) conducted power adequacy studies. ENTSO-E (2014), North American Electric Reliability Corporation (2011), Pentalateral Energy Forum (2015) and Australian Energy Market Operator (2013) presented chronological methods in their reports. VTT (2014) and PJM (2003) applied a frequency distribution method, whereas the report 2015 Scenario Outlook & Adequacy Forecast (ENTSO-E 2015b) an approximation method.

All of the selected reports seem to be unanimous that the growth of the share of intermittent energy sources in the energy mix is a driver for hourly probabilistic methods in adequacy analysis. PJM (2003) was the only report which did not emphasize on the need for chronological methods. North American Electric Reliability Corporation (2011) indicated, however, that studies which do not use chronological methods may not correctly measure the system loss of load probability. The chronological method takes into account the correlation between weather dependent factors as the temperature, wind and precipitation, which cannot be taken into account with the frequency distribution method.

The monitored adequacy indices varied between the reports. The report 2015 Scenario Outlook & adequacy Forecast (ENTSO-E 2015b) and PJM (2003) only monitored a reliability index, which was capacity margin or LOLP. However, all of the chronological methods (Pentalateral Energy Forum 2015, NERC 2011, ENTSO-E 2014, AEMO 2013) and VTT's frequency distribution method (2014) reported most of the main reliability indices, as ENS, LOLE and LOLP. An overview of the methodologies of the selected generation adequacy studies is presented in Table 2.

Table 2: An overview of the methodologies of the selected generation adequacy studies and methodologies

Report	Method	Simulation	Resolution	Index
SOAF (ENTSO-E 2015a)	Approximation	Scenario	Peak hour	Capacity margin
Selvitys tehoreservin tarpeesta vuosille 2015–2020 (VTT 2014)	Frequency distribution	-	Hourly	LOLE, LOLP
PJM Generation Adequacy Analysis: Technical Methods (PJM 2003)	Frequency distribution	-	Weekly peak hour	LOLP
Generation adequacy assessment report (Pentalateral Energy Forum 2015)	Chronological	Monte Carlo	Hourly	ENS, LOLE, Remaining capacity
ENTSO-E target methodology for adequacy assessment (ENTSO-E 2014)	Chronological	Monte Carlo	Hourly	LOLE, LOLP, full load hours, RES curtailment
Methods to Model and Calculate Capacity Contribution of Variable Generation for Resource Adequacy Planning (NERC 2011)	Chronological	Monte Carlo	Hourly	LOLE, LOLP, ENS,
Energy Adequacy Assessment Projection (AEMO 2014)	Chronological	Monte Carlo / Scenario	Hourly	ENS

2.5.2 Modeling of Input Parameters

There are differences between the adequacy analysis methods, how the uncertainties of modeling parameters are taken into account. The common modeling parameters which influence power adequacy are discussed below.

As stated in Section 2.4, there are two main ways to model these variables: deterministic and stochastic. The deterministic way of modeling means that the uncertain variable is assigned a value or a couple estimated values according to a chosen scenario, as stochastic modeling assigns a variety of possible values, for example according to historical values from a long period of time or through random number generation.

The report 2015 Scenario Outlook & adequacy Forecast (ENTSO-E 2015b) used deterministically best estimate and conservative scenarios which included estimations in the development of the generation mix, load forecast. The available wind and solar generation capacity profiles were based on a separate weather analysis. The faults and the unavailability of generation capacity were modelled with a scenario that was obtained from the results of previous probabilistic adequacy studies. The input data was harmonized European wide, which means that all data was collected from the same hour of the year.

The other examined reports used stochasticity in their modeling of input parameters. Table 3 shows an overview if and how stochasticity was implemented in the selected adequacy studies and methodologies. The table illustrates that each report harmonized the weather dependent parameters.

Table 3: *Stochastic modeling of the input parameters of the selected stochastic adequacy studies and methodologies*

Report	Demand	Wind	Solar	Hydro	Harmonized input	Outages
Pentalateral Generation Adequacy Assessment (Pentalateral Energy Forum 2015)	Yes	Yes	Yes	Yes	Yes	Yes
ENTSO-E target methodology for adequacy assessment (ENTSO-E 2014)	Yes	Yes	Yes	Yes	Yes	Yes
Selvitys tehoreservin tarpeesta vuosille 2015–2020 (VTT 2014)	Yes	Yes	No	Yes	Yes	Yes
Methods to Model and Calculate Capacity Contribution of Variable Generation for Resource Adequacy Planning (NERC 2011)	Yes	Yes	Yes	Yes	Yes	Yes
Energy Adequacy Assessment Projection (AEMO 2014)	Yes	No	No	Yes	Yes	Yes

The study conducted by Pentalateral Energy Forum (2015) applied a stochastic Monte Carlo simulation method for the analysis of European adequacy. The method improved previous European deterministic analysis methods and therefore is a good reference for stochastic, chronological adequacy analysis in Europe. Its method is presented below in detail.

There were a total of 220 Monte Carlo years simulated in the study. The years were created from combining three different categories: hydro years, weather years and outages. There were 3 different hydrological years, with a representative probability of occurrence, the normal year of having 0.8, wet and dry year having a probability of 0.1 each. There were 11 weather years, which included load, wind and solar profiles. The weather years were based on the historical years 2000–2011 and were regional-widely harmonized. The temperature sensitivity of demand was applied as input in correlation with solar and wind time series. The representative hydro years were not harmonized with other weather data. The outages and maintenances formed the third category. The profiles of the category were implemented with a probabilistic tool. The rate of availability was based on the type and the fuel of the unit, in addition to the historically observed forced unavailability.

2.5.3 Main Findings

The study by Pentalateral Energy Forum (2015) acknowledged further development needs in its methodology. The report stated that stochastic availability profiles should also be created for interconnectors. Optimized hydro modelling was not used in the study, which can especially affect hydro-based systems. The study acknowledged the need for additional climatic years. The report used 11 climatic years with only 3 hydro years. The modelling of demand side response and grid constraints was also seen as a target for development.

North American Electric Reliability Corporation (2011) named three factors that should be taken into account in today's power adequacy analysis. Firstly, the transmission capacities have a significant effect on adequacy. Secondly, intermittent energy sources need hourly time dependent chronological approaches. Variable generation may increase the risk of curtailment even in daily hours, which are not daily peak hours. Selecting a single daily peak hour for assessment may provide an inaccurate picture of power adequacy. Thirdly, energy modeling programs with hourly resolution are needed. New generation capacity does not necessarily correspond to increased energy adequacy. The simplified capacity margin method does not sufficiently indicate the energy adequacy of a system with high amount of intermittent energy sources. Energy modeling programs can conduct complex power system analysis, which allows a detailed probabilistic adequacy assessment.

3 Characteristics of the Baltic Sea Electricity Market

This chapter describes the main characteristics of the Finnish electricity market and the Baltic Sea electricity market. The chapter focuses on the characteristics which are relevant to the power adequacy of Finland. Both short-term and long-term aspects are included in the discussion.

3.1 Power Capacity

Finnish generation capacity mostly consists of nuclear power, hydro power, combined heat and power and condensing power (Figure 3). Fossil fuels and biomass columns are composed from CHP and condensing power. The figure shows the energy share and the capacity share of the different production types of Finland. (ENTSO-E 2015b)

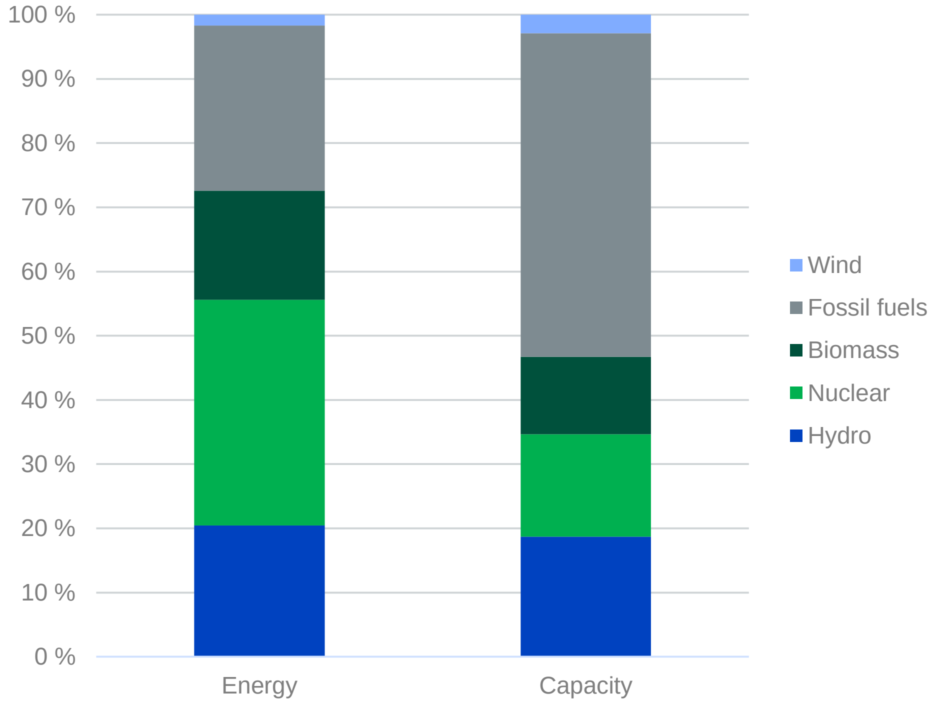

Figure 3: *The Finnish energy and capacity mix as a percentage of total energy and capacity in 2014 modified after (ENTSO-E 2015b)*

Pöyry (2015) published a report on the generation adequacy of Finland. The report examined the current state and the expected future of Finnish energy market. According to the study, the available generation capacity is considerably lower than the total generation capacity during peak hours. The estimated total generation capacity was 15 500 MW, however, only having a capability of producing 12 500 MW during peak hour at the end of 2014. Nuclear and condensing power was expected to produce electricity at rated power. Generation constraints and system service reserves were expected to decrease the generation capacity of hydro power. The wind power capacity was estimated at 6 % from the total capacity at peak hour. The peak hour capacity of district heating producing CHP was claimed to decrease 15 % during peak hour. An increased need for district heating decreases the electricity production capability of the units. Also, the industrial CHP capacity was expected to be lower than rated power. The size of the industrial CHP electricity was assumed to correlate with the ongoing economic situation. (Pöyry Management Consulting Oy 2015)

There is especially uncertainty in the future of fossil fuel generation capacity and wind power capacity in Finland. Pöyry (2015) agreed with the report by department of industrial management Åbo Akademi (2015) that CHP is losing profitability with the current, low market prizes. Åbo akademi (2015) identified subsidized wind power, mild winter temperatures and rainy years as the main reasons for the low prices during the past few years. It is possible that future district heating investments would focus on separate heat production instead of CHP. Therefore, the capacity of CHP and condensing power was assumed to decrease in the future. (Pöyry Management Consulting Oy 2015)

During the years 2013-2015, 2 085 MW of condensing power have been dismantled in Finland (Nord Pool Spot 2015b). If electricity prices continue being low, more unprofitable condensing power may be dismantled during the upcoming years. The share of wind power was assumed to continue to increase. The target of Energy and Climate strategy for electricity produced by wind power is 9 TWh in Finland by 2025. (Pöyry Management Consulting Oy 2015)

In 2015, there were four nuclear units in Finland; two in Loviisa (992 MW total) and two in Olkiluoto (1 760 MW total). A new unit is built in Olkiluoto (1 600 MW). The operation permits of the reactors in Loviisa end in 2027 and 2030. (Pöyry Management Consulting Oy 2015) A unit applied for a construction license of 1 200 MW in Hanhikivi in 2015 (TEM 2015).

The most of the hydro power plants in Finland are run-of-river. This means that the plants have a weak or non-existing storage capability. (Energiavirasto 2014) The amount of hydro power capacity is assumed to stay unchangeable in the coming years in Finland, since most of the potential new hydro capacities are located in protected waters (Pöyry Management Consulting Oy 2015).

The Baltic Sea Electricity Market consists of Nordic and Baltic countries, Poland and Germany. The share of electricity generation in each country in 2014 is presented in Figure 4. Most of the hydro resources are located in Norway, Sweden and Finland. The maximum capacity of the hydro reservoir is about 121 TWh in the Nordic countries (Energiavirasto 2014, p. 6) which is almost third of the total electricity consumption (380 TWh in 2013) in the Nordic region (Nordic Energy Regulators

2014, p. 3) The share of the total reservoir capacity in Finland is quite minimal, only about 5.5 TWh (Energiavirasto 2014, p. 6).

Norway holds the most significant amount of hydro resources and produces almost all of its electricity with hydro power. The electricity production of Sweden is based on nuclear and hydro power. In Sweden, the share of wind power is already notable. Denmark produces almost half of its electricity with wind power and the other half with fossils and biofuels.

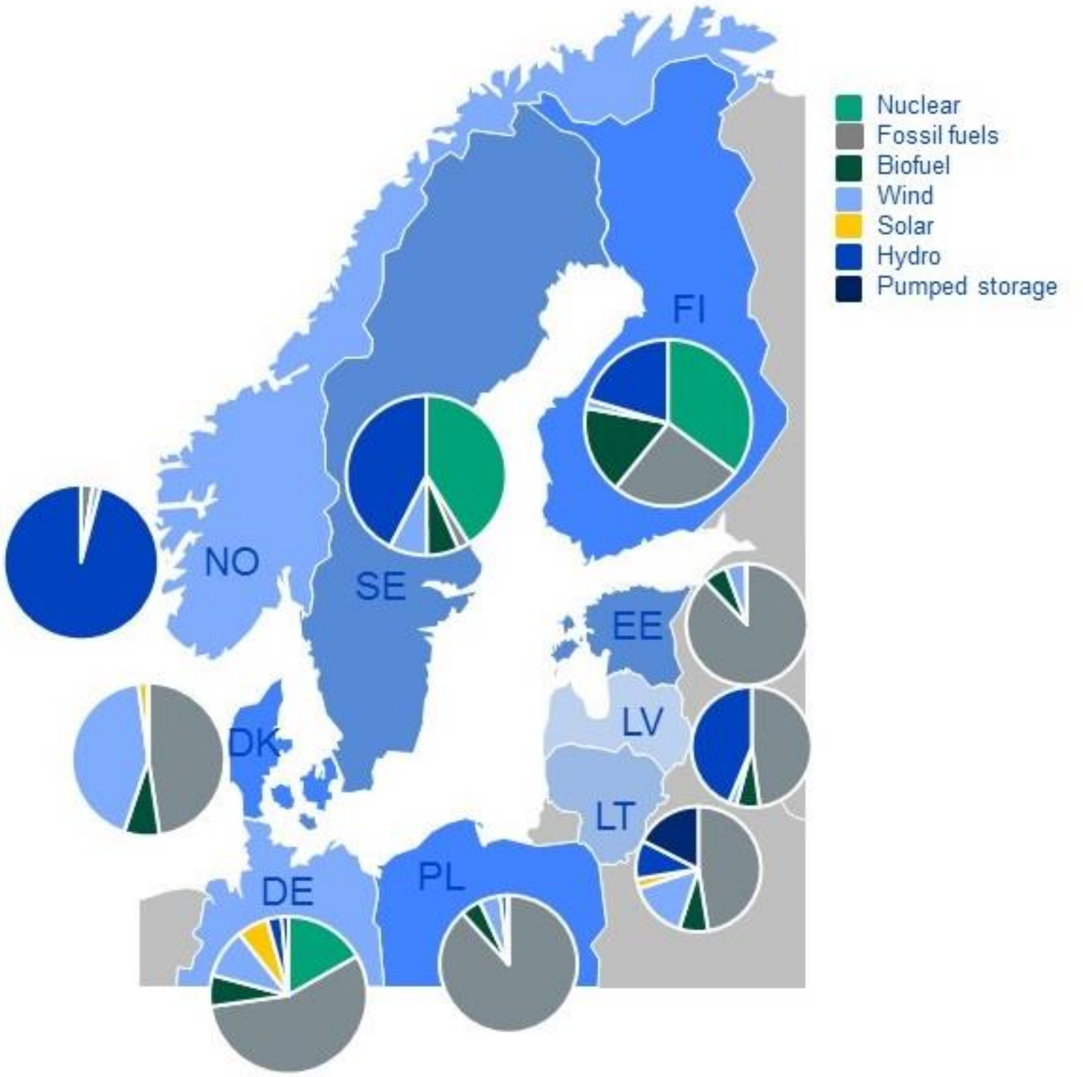

Figure 4: *The electricity mix of the countries in the Baltic Sea Market Area in 2014 modified after* (ENTSO-E 2015b)**.**

ENTSO-E's report (2015b, p. 76) presented estimations on the future of the power system of Sweden. The report expected the generation capacity of nuclear power to decrease due to decommissioning. The net generating capacity of fossil fuels was expected to decrease, while the capacity of wind power and biomass to increase. Existing fossil fuel plants have been refitted to biomass, which was seen to continue in the future.

The power capacity in the Baltic countries - Estonia, Latvia and Lithuania - is mostly based on conventional fossil fuels (Figure 4). According to ENTSO-E's report (2015b), the capacity of conventional fossil fuel is expected to decrease both in Estonia and in Lithuania due to aging power plants by more than 1000 MW in total between the years 2016–2025. Latvia has a significant amount of hydro resources, producing almost half of its electricity with hydro power on an average year. Lithuania has a notable pumped storage plant.

Germany and Poland produces most of their electricity with fossil fuels (Figure 4). The share of wind and solar power is already significant in Germany and the ENTSO-E's report (2015b) stated that the share is expected to grow accompanied by supportive legislation. In Germany, nuclear phase-out was expected to be completed in 2022. ENTSO-E (2015b) expected the growth of renewables to yield to the close-downs of conventional power plants in Germany.

Different electricity sources contribute differently to generation adequacy. All new generation capacity can be seen to influence positively into generation adequacy. When wind power replaces conventional power generation, the net effect is typically negative. This is a result from the challenges of wind intermittency and long-term wind forecasting, since it is difficult to determine how much wind power will be actually available as generation capacity at all times. (VTT 2014)

3.2 Electricity Demand

Pöyry's report (2015) on generation adequacy also discussed the current and the future state of electricity demand and factors which affect the development of demand in Finland. Its findings are presented below. The report stated that the generation capacity in Finland is not sufficient to meet the demand during peak demand hours. During those hours, Finland is dependent on imports from its neighboring countries. According to the scenario analysis of the study, the generation capacity of Finland was not sufficient in any analyzed scenario in 2014–2030.

In the future, the total yearly demand of Finland was expected to grow mildly. For power adequacy purposes, the development of peak demand and the shape of the demand profile is more important than the total yearly demand. The development of peak demand is dependent on the total yearly demand but also on the changes in the demand structure which reflects in the demand profile. Electricity demand can be categorized into five separate sectors:

- households,
- electric heating,
- transportation,
- services and
- industry. (Pöyry Management Consulting Oy 2015)

Pöyry (2015) expected the net electricity consumption of households, heating and transportation to grow. The growth of the amount of households was estimated to surpass the household energy efficiency measures. Electric heating as a heating option and the need for cooling equipment was seen to increase in the future. The electricity consumption of the transportation sector would increase if electric cars became more common.

The consumption of the service sector was not expected to increase substantially. There is large potential in energy savings measures, which will restrain the increasing consumption resulting from the development of the service sector. The Finnish electricity consumption is highly influenced by industrial electricity use, since the industry in Finland is electricity intensive. The development of industrial electricity use depends highly on the general economic growth in Finland. (Pöyry Management Consulting Oy 2015)

The hourly profile of industrial consumption is more flat than the profiles of other sectors. If industrial consumption increases more rapidly than other sectors, the relative hourly demand profile variation is smoothened between seasons.

Pöyry (2015) stated that electric use for heating determines the size of the peak demand at the moment. The increase of electric heating would rise the demand peaks during cold winter days. On the other hand, the use of cooling equipment would increase the electricity consumption for heating during the summer. Pöyry argued that charging of electric cars both can smoothen out the demand profile in the morning as well as increase the peak demand during the evening in the future.

Demand Side Response (DSR) transfers the consumptions of electricity from high price hours to low price hours. The total amount of electricity consumption does not change, but the demand is decreased during peak demand hours. (Pöyry Management Consulting Oy 2015, p. 40) The amount of demand side response was estimated at 200–600 MW at the day-ahead markets in Finland in 2016 (Fingrid Oyj 2016b).

ENTSO-E's report 2015 Scenario Outlook & adequacy Forecast (2015b) discussed the power adequacy situation currently in European countries according to a study conducted. The results concerning the countries in the Baltic Sea Electricity Market Area are presented below. A mild growth of the peak demand was expected in all countries.

In Sweden, electricity consumption is closely linked to economic activity and a surplus of power in 2016 was expected for the most of the time. In Norway, there is a surplus of 5–16 GW available for export in 2016. A slow growth in load and demand is forecasted for the next 10 years, with the same amount of growth in generation resulting in a similar surplus for the next years. During winter, the surplus decreases because of higher demand in Norway.

On the other hand, Denmark has a deficit which is covered by interconnectors to neighboring countries. Estonia is mostly self-sufficient during peak demands and possible shortages are expected to be covered by imports. Lithuania relies on energy imports most of the time, whereas Latvia is self-sufficient. In Poland, the peak demand was expected to increase faster in the summer period than during the winter period.

3.3 Transmission Lines between Finland and its Neighbors

Finland is connected to Sweden, Estonia and Russia with interconnectors (Figure 5). There are a total of 5 100 MW of import capacity to Finland from its neighboring countries. Between Finland and Sweden, there are two submarine High Voltage Direct Current (HVDC) connections, Fennoskan 1 and Fennoskan 2, in addition to two 400 kV AC overhead lines. Fennoskan 1 and 2 connects Swedish bidding area SE3 to southern part of Finland with a total capacity of 1 200 MW. The overhead lines are located between Swedish bidding area SE1 and northern Finland. The import capacity of the overhead lines to Finland is 1 500 MW and the export capacity from Finland to Sweden is 1 100 MW. (Fingrid Oyj 2016f)

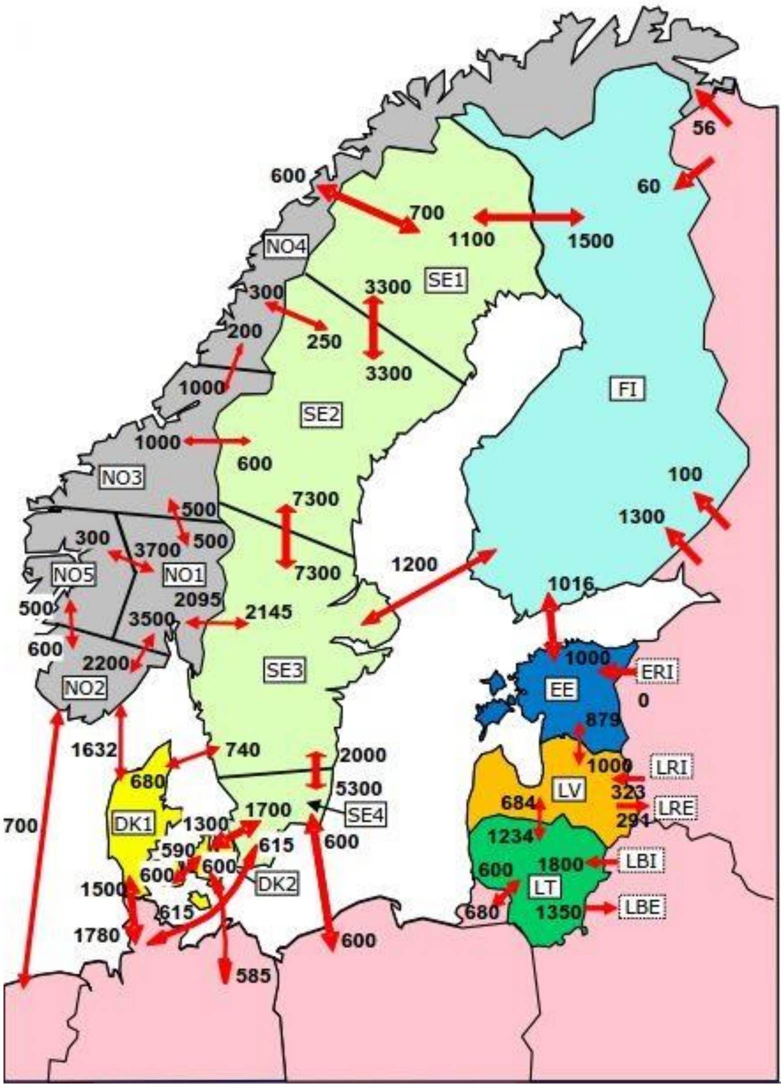

Figure 5: *The commercial maximum net transfer capacities of interconnectors in the Nordpool Spot Market Area in 2015 (Nord Pool Spot 2015a)*

Estlink 1 and Estlink 2 were commissioned between Finland and Estonia in 2007 and 2014 respectively. The connections are submarine HVDC cables with a total importing capacity of 1016 MW to Finland. The Vyborg back-to-back HVDC cable connects Finnish and the north-west Russian grid. The commercial import capacity of the Vyborg connection to Finland is 1300 MW. (Fingrid Oyj 2016f) Until 2015, exporting electricity to Russia was not possible via Vyborg connection. From the beginning of 2015, an export capacity of 320 MW to Russia was given to the market (Fingrid Oyj 2014).

Finland is connected to the Central European market area through its neighbors. Sweden has connections to Norway, Denmark, Germany and Poland (Figure 5). In addition, there are other ongoing investment plans to strengthen the connections from Scandinavia to Central Europe. (Pöyry Management Consulting Oy 2015, p.30) In 2016, Nordbalt was commissioned, which is a submarine HVDC cable that connects Sweden and Lithuania. A HVDC interconnection between Lithuania and Poland was commissioned in 2016 with a maximum transmission capacity of 500 MW. The connection adds another route from Finland through the Baltic countries to the Central Europe. (Nord Pool Spot 2015c)

Interconnector capacity does not necessarily mean that the neighboring countries have excess electricity for export during peak demand periods in Finland. Pöyry (2015, p. 35) stated that the unpredictable outages and faults of power plants and interconnectors affect the import capacity of interconnectors more than the shortage of energy due to weather conditions.

VTT (2014, p.17–20) studied the effect of weather conditions on importing electricity with interconnectors to Finland. The study examined the correlation of extreme cold occasions between Finland and its neighbors. In addition, it compared the estimated amount of peak demand and peak generation. According to the study, the importing capacity from Sweden was always fully available during peak demand periods if imported electricity from Norway was taken into account. Excess capacity was assumed both in Sweden and in Norway during Finnish peak demand periods.

On the other hand, the import capacity from Estonia was not estimated to be fully available during peak demand hours. An import capacity between 460 MW and 690 MW was estimated before the commissioning of Nordbalt. After the commissioning, the import capacity was assumed to be fully available. This means that there is not enough excess capacity in the Baltics alone for exporting to Finland during peak demand periods. Electricity import from Russia, Poland or Sweden to the Baltics was needed for full capability. The Baltic countries, Estonia, Latvia and Lithuania are connected to each other's with interconnectors, which is why the balance of the whole Baltic system affects the exporting capability of Estonia to Finland.

4 Power Market Simulator

This chapter provides a brief overview of the characteristics a general power market simulation tools (software), hereafter referred as power market simulators. The chapter presents two commercial software examples.

4.1 General

Power market simulators are used as a tool in analyzing and forecasting the electricity markets. Simulation tools are commonly used by electricity producers, transmission system operators and other market players. Transmission system operators use the power market simulators typically as a tool for creating transmission forecasts and cost-benefit analysis on grid investments. (Fingrid Oyj. Laasonen & al. 2011)

The power market simulator models the electricity market with separate areas which are connected together with transmission lines, interconnectors (Fingrid Oyj. Laasonen & al. 2011). Each area is given various input about the electricity market, including information about the production capabilities and demand of the area. The type of input data differs between the tools. The tool solves the supply and demand optimization problem of the whole electricity market within the limits of the given input data. Various output can be derived after the simulation.

4.2 Samkjøringsmodell

Samkjøringsmodell is a power market simulator provided by SINTEF. It is suitable for modelling hydro-based electricity markets, because of its detailed description of hydro power plants. Samkjøringsmodell, also referred as EMPS (EFIs Multi-area Power Scheduling Model), was originally developed for optimizing hydro production. Now, it can be used for various purposes in analyzing electricity markets. (Fingrid Oyj. Laasonen & al. 2011)

EMPS is based on minimizing the production costs of electricity in a perfect electricity market. Perfect electricity market presumes that all market players offer all available production capacity at marginal cost. The model comprises two calculation stages. During the first stage, water values are calculated for the storage reservoir of each area. Water values can be compared with the marginal costs of other production types. The second stage is the actual simulation part, where the supply curve of the production is formed according to the marginal costs of each production type. (Fingrid Oyj. Laasonen & al. 2011) The model solves the optimization problem each week with an up to an hourly time resolution. (SINTEF 2015)

4.3 BID

BID is a power market simulator currently provided by Pöyry. BID is suitable for modeling a thermal power based market with hydro power, because non-linear thermal restrictions are taken into account in the model. (Fingrid Oyj. Laasonen & al. 2011) Fingrid uses an advanced version, BID3.

BID3 also calculates water values for reservoir regions, but the overall modeling of hydro power is more aggregated. On the other hand, the modelling of thermal power production takes into account non-linear restrictions, for example start-up costs, minimum stable generation, ramping and minimum on and off times. (Fingrid Oyj. Laasonen & al. 2011, Pöyry Oyj 2015)

BID3 calculates the optimization problem on an hourly time resolution. A benefit of hourly resolution is especially the detailed modeling of intermittent energy sources and demand. Demand, wind and solar power can be modeled with historical hourly series, which is suitable for stochastic modeling of power adequacy analysis (Pöyry Oyj 2015).

5 Power Adequacy Analysis by a Power Market Simulator

This chapter presents the proposed adequacy analysis method. The chapter discusses the chosen method and the modeling of stochastic parameters. A new method is introduced how unplanned outages can stochastically be modeled. The last part combines the different components of the proposed method together and presents a comprehensive method for adequacy analysis.

5.1 The Monte Carlo Simulation Method

In this study, all the simulations are run with Pöyry's power market simulator BID3 version 3.1.3. As discussed in Section 4.3, BID3 can model electricity markets with an hourly resolution and can be used, for example, to extract results containing the traditional adequacy indices. The tool has a built-in case collection module, which can be applied to performing a Monte Carlo analysis.

The Monte Carlo method is a name for stochastic simulation, where a series of experimental simulations are created using random numbers. This is done usually by random sampling. (Wenyuan 2014, p. 489). The Monte Carlo simulation can be used for system reliability and availability modeling when using suitable computer programs (O'Connor, Patrick & Kleyner, Andre 2011).

Byrne (2013) discusses that a stochastic model has an infinitely large population and therefore it is not possible to run all the possible states of the population in his article. That is why sampling must be done and some uncertainty of the true prediction of the model must be tolerated. According to the central limit theorem, the sample mean is the best estimate for the sample when the number of samples is large enough. The variance of the sample indicates how accurate the estimation is. (Wenyuan 2014, p.489)

There are mathematical theories and practical methods for evaluating the sufficient number of Monte Carlo simulations in a sample. Byrne (2013) explained three different approaches how to evaluate it. With the first, simplistic approach, the model is run until the mean converges. It can be noticed when additional model runs do not change the mean of the model estimation notably. However, the approach is often applied when it is possible to run thousands or tens of thousands of model runs. The second approach was based on models of proportions. The approach requires the estimation of the proportion of trials correct which would be difficult to make in a power system simulation application.

A third approach is based on confidence intervals. It is a statistical construct that provides information of the parameter based on the average and the variance of the sample. These parameters are easy to extract from any statistical result. The only set-back is that the confidence interval cannot be evaluated before the simulations have been run. (Byrne 2013) In this study, the first and the third approach were used in the convergence case study. However, the third approach is suggested for the proposed method since it is applicable to any statistical results and provides results that are easy to interpret. The method is explained in detail in Section 5.4.

5.2 Stochastic Modeling of Outages

5.2.1 Introduction

Previous studies (sub-section 2.5.3) indicated that there is still further development needs in the stochastic outage modeling of the power plants and interconnectors. As the Finnish power system is dependent on the importing capacity during peak demand hours, the availability of interconnectors is an important factor for the Finnish power adequacy. Pöyry (2015) found out that the available import capacity of Finland from the neighboring countries is affected more by the outages of power plants and interconnectors than the shortage of energy due to weather conditions during peak demand periods. This points out that the modeling of outages is as important as the modeling of weather conditions or even more important.

The problematic nature of availability modelling lies in the stochasticity of outages. The market does not know beforehand, when an outage occurs and how long it lasts. 2015 Scenario Outlook & adequacy Forecast (ENTSO-E 2015b) modeled the availability of units with a chosen scenario, whereas Pentalateral Energy Forum (2015) implemented the availability profiles stochastically with a probabilistic tool. There are problems with a deterministic, chosen scenario way of thinking, as discussed in Section 2.4. A chosen scenario does not necessarily represent the whole phenomena widely enough. The tool by Pentalateral Energy Forum (2015) applied a different availability profile for each simulated Monte Carlo year for each unit. The profile was created based on the type and fuel of the unit, in addition to historically observed forced unavailability.

The probabilistic random number sampling method was chosen in this thesis. A power shortage may be a result of many improbable, but still possible, events occurring simultaneously. Therefore, the outages should be accounted with their representative probability. The stochasticity can be implemented with a tool which was developed in this thesis. The tool is explained in the next section.

5.2.2 Input Parameters

In this thesis, a tool was created which generates stochastic, chronological availability profiles for power plants and interconnectors with a random sampling method. It was implemented with Excel's Visual Basic module. The algorithm is presented in Appendix A. The power plants and interconnectors were divided into different categories according to the power plant and interconnector type. While the division by Pentalateral Energy Forum (2015) was based on the type and fuel of the unit, the categories were purely divided according to the type of unit in this study.

Each category was given different initial parameters, which affect how the tool generates random outages. The purpose of the division into the categories was to describe how some power plant and interconnector types are more prone to outages than others. For example, according to Pöyry's study (2015), a fault is more probable to occur in a condensing power plants than in a CHP power plant in Finland. This is because many of the condensing power plants are operated discontinuously and started up frequently to match peak demand periods in Finland, which increases the risk of an occurring fault.

Forced outage rate is a widely used input parameter for outage modeling. It can be used as the only input for creating binomial hourly availability profiles. This means that the hourly availability profile is created by inserting zeros and ones randomly, where zero indicates the unavailability and one the availability of a unit. The sum of ones in the profile should correspond to the given forced outage rate. The method is widely used in the field of study since it is easily implementable. However, the binomial method does not take into consideration that an occurring fault has a tendency to last for multiple hours. This characteristic requires chronological properties from the tool, which is why the binomial method was not used in this study.

The forced outage rate alone does not give enough information on how to generate an hourly, chronological availability profile for a specific unit. A yearly outage rate of 5 %, can consist of multiple short faults or a couple of long lasting faults. In this thesis, a chronological method was created, which allows these distinct cases to be differentiated. The method involves giving each category three initial parameters:

- average number of outages per year,
- average duration of an outage and
- standard deviation of the duration of the outage.

The average number of outages determines if a category is prone to a few or many faults during a year. This parameter treats short and long lasting faults the same, which is why two additional parameters were needed. The average duration of an outage describes how long the usual repair time of the unit is and the standard deviation describes how spread out the separate fault durations can be.

The initial parameters used for each category were estimated according to the Nord Pool Spot UMM system (Nord Pool Spot 2015c) in this thesis. The parameters were derived from published maintenances and faults for units during 2013 and 2014. In order to get statistically more precise initial parameters, they should be derived from a longer time period than two years. However, the data availability was limited to two years, at the time of this study. The used data was still able to depict differences in the initial parameters for the main categories, which was the main purpose of the development of the method. The initial parameters used in this study can be seen in Table 4. HVDC and AC input values were related to the interconnector outages.

Table 4: *The input parameters used for fault frequencies and fault durations related to each category*

	Fault frequency	Fault duration	
Type	**Average occ/year**	**Average (h)**	**Standard deviation (h)**
Finnish CHP	7.6	51	264
Finnish Condensing	11	70	309
Finnish Nuclear	7.0	21	65
Swedish Nuclear	8.3	113	437
HVDC [1]	4.9	64	1019
AC	3.1	58	54

[1] An estimation based on CIGRE's statistics of the reliability of HVDC systems throughout the world.

5.2.3 Functionality

The functionality of the stochastic availability profile tool can be divided into three parts.

1. Check if an outage occurs
2. Select a size for the outage
3. Randomize a duration for the outage

The first part is based on a point estimate and the third on a probabilistic distribution function approach. The outages of individual generation units are considered statistically independent in the tool.

The occurrence of an outage is implemented with an acceptance-rejection method (NAG 2012). The acceptance-rejection method assumes that an outage is equally likely to occur during any hour of the year. A unit has a probability of a fault occurring p_{occ} which is characteristic of the category type. The tool generates a random number, y, between zero and one each hour of the year with Excel's random number generation function. If y is greater than p_{occ}, an outage occurs at the specific hour. If y is smaller, the unit is in service and the function moves on to the next hour. Each hour is considered as an independent event, which means that the previous state does not affect the state of the next hour unless a fault occurs. The probability $p_{o\mathrm{cc}}$ is calculated with eq. (1)

$$p_{\mathrm{occ}} = 1 - \frac{n_{\mathrm{fault}}}{8760}, \tag{1}$$

where n_{fault} is the average number of faults occurring during a year.

The second part of the tool randomizes a duration for the occurring fault. The fault duration is an integer number generated randomly from a cumulative distribution function of the inverse log-normal distribution. The log-normal distribution was chosen to describe the duration of the fault because of its characteristics. The distribution is often used to model repair time of a maintained system, since it is more versatile than the normal distribution and it only generates non-negative values (O'Connor, Patrick & Kleyner, Andre 2011)

The log-normal distribution function can be calculated with eq. (2)

$$f(x) = \frac{1}{x\sigma\sqrt{2\pi}} \exp(-\frac{(\ln x - \mu)^2}{2\sigma^2}). \tag{2}$$

The log-normal distribution function is a normal distribution with the natural logarithm of x as the variate. Note that μ and σ are not the mean nor the standard deviation of the log-normal distribution. The mean and the standard deviation of the log-normal distribution are given equations (3) and (4) respectively by

$$\mathrm{E}(x) = \exp(\mu + \frac{\sigma^2}{2}) \tag{3}$$

$$SD(x) = \sqrt{\exp(2\mu + \sigma^2)(\exp(\sigma^2) - 1)}\ . \tag{4}$$

Parameters μ and σ in the equation (2) can be calculated respectively by (Wenyuan 2014)

$$\mu = \ln(\frac{E^2}{\sqrt{SD^2+E^2}}) \quad (5)$$

$$\sigma^2 = \ln(\frac{SD^2+E^2}{E^2}). \quad (6)$$

Given that the outage duration of power plants and interconnectors is assumed log-normally distributed, then, the inverse of the cumulative log-normal distribution returns the outage duration corresponding to each percentile of a unit Normal distribution.

The inverse cumulative log-normal distribution function takes three parameters: μ, σ and a percentile at which the function is evaluated (NAG 2012). The percentile corresponds to the value below a given percentage of observations fall. Parameters μ and σ can be calculated with the equations (5) and (6) respectively with the mean and the standard deviation of the duration of the fault. The parameters were specific to a unit category and are given as input to the tool. The percentile was generated with a random number generator.

Next, an example of the random fault duration generation is presented. A category has μ and σ of 2 and 0.2 respectively. Two separate faults are considered for this example. Figure 6 shows an inverse cumulative log-normal distribution with the given mean and standard deviation. A random percentile is generated for each fault, for example, 0.2 for the first fault and 0.5 for the second. With these assumptions, 20th percentile corresponds to a fault duration (x) of 6.2 hours and 50th percentile corresponds to the median value of the distribution, which is approximately 7.4 hours. The tool would, thereby, set a fault duration of 6.2 hours for the first fault and 7.4 hours for the second fault.

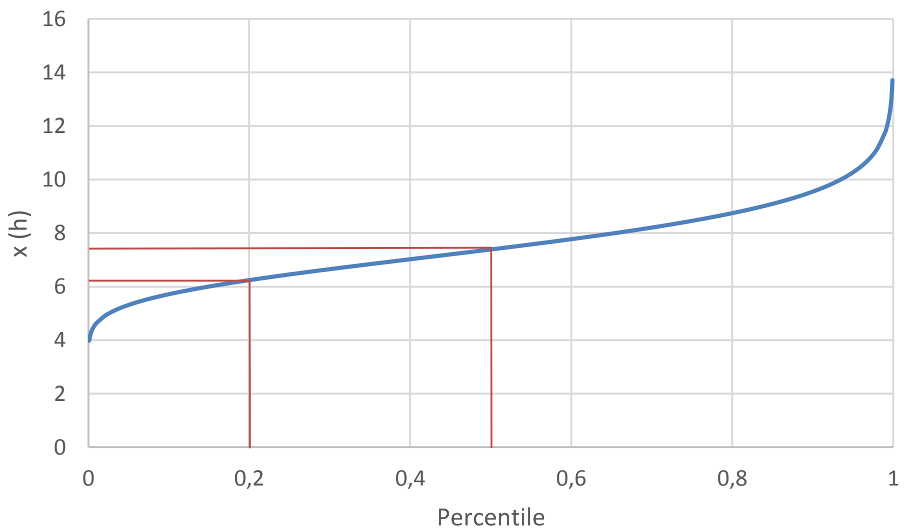

Figure 6: *The inverse of Log-Normal Cumulative Distribution of x with μ = 2 and $\boldsymbol{\sigma}$ = 0.2.*

Each unit was also given allowed fault sizes into the tool as input. The effect of a fault on the available capacity of a unit can be very different. Some faults can set the whole unit as out of service and some faults only a part of it. This characteristic is especially important for aggregated power plants or aggregated interconnectors. It would be unrealistic to set the aggregated unit as out of service each time a fault occurs. Each unit was given a single allowed fault size or multiple allowed fault sizes and each allowed fault size had an equal probability of occurring.

Table 5 shows an example of the modeling of fault sizes. CHP and Coal Power Plant units have been given a fault size which corresponds to the maximum capacity of the units. When a fault occurs, the whole unit will be set as out of service. Nuclear is an aggregated unit, which consists of two different 500 MW power plant units. Therefore, it is given two different fault sizes which correspond to the sizes of each representative unit and the occurrence of each fault is independent. This way the occurrence of the other fault does not affect the probability of the other fault occurring.

AC interconnector is an interconnector between two bidding areas which consists of multiple lines. The unit is given two 200 MW fault sizes, even though the maximum capacity is 1000 MW. The example shows that the sum of the fault sizes in the tool can be less than the maximum capacity.

Table 5: *A general example of the modeling of different fault sizes occurring*

Unit name	Type	Max Cap (MW)	Fault 1	Fault 2
CHP	CHP	100	100	
Coal power plant	Condensing	200	200	
Nuclear	Nuclear	1000	500	500
AC interconnector	AC	1000	200	200

Lastly, after the duration of the fault and the size are implemented in the availability profile, the function moves on to the next hour after the last hour of the occurred outage, where it changes the status of the hour back to in service. Then the tool continues with the acceptance-rejection method test. The whole process of the tool is shown in Figure 7.

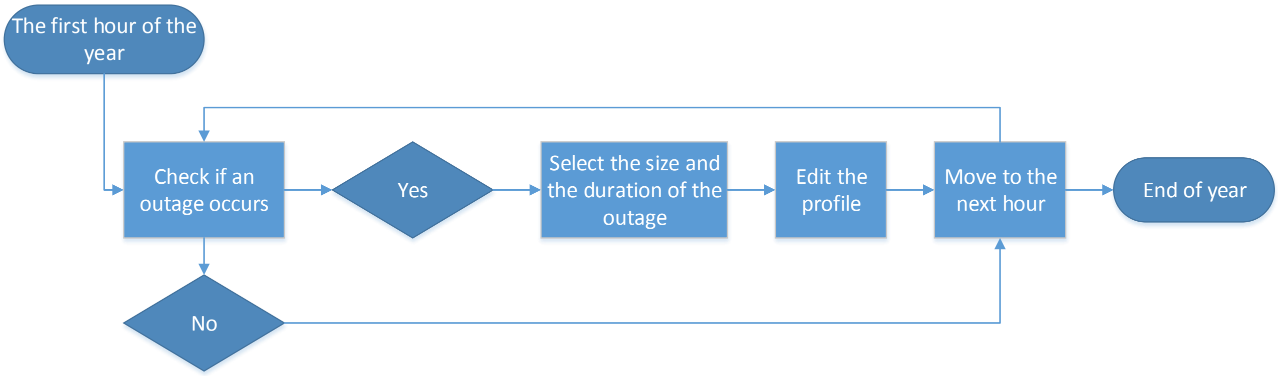

Figure 7: *The depiction of the stochastic availability profile generator*.

The tool also takes planned maintenances and outages into account. Most plants and interconnectors have planned yearly maintenances which should be included in the final hourly availability profile. The information about the planned maintenances was given as input to each unit. Figure 8 presents an example of the tool output. A planned maintenance can be seen between the hours 1700 and 4100. Other smaller gaps are outages generated by the stochastic tool. Each time the tool is run, the occurrences of the outages are different since the tool is based on a random number generation. The inverse logarithmic function ensures that the duration of the faults are represented with representative probabilities.

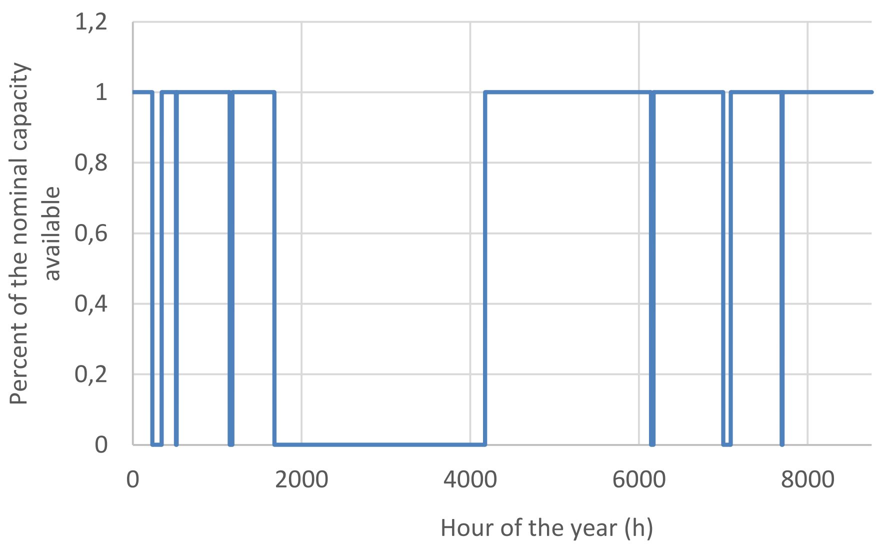

Figure 8: *An example of the output of a randomized hourly availability profile for a unit. The tool creates an hourly availability profile which consists of possible planned maintenance and faults which are generated randomly. The random fault duration is generated according to an inverse logarithmic function. The fault size is selected according to the given input.*

5.3 Weather Dependent Parameters

Demand, CHP must run, hydro inflows and wind power were modeled with stochasticity with an hourly resolution in this study. **Solar power** is also acknowledged as an important weather dependent parameter to be included with stochasticity in the future. At the moment, the capacity of solar power is marginal in Finland, why it was not modelled with stochasticity in this thesis.

Hourly demand and CHP must run profiles were based on meteorological temperature data. Figure 9 illustrates the variance of the daily mean temperatures of Helsinki during the years 1962–2012. The data on the figure was acquired from the open data datasets of the Finnish Meteorological Institute (Finnish meteorological Institute 2015). For example, the bottom yellow area shows the coldest five percent of the daily mean temperatures that have been observed during each day of the year. The figure shows that the temperature of Helsinki variates significantly yearly. Also, it can be seen that the variance is greater during the winter months than during the summer months. For example, the daily mean temperatures have been observed from under -30 °C to more than 6 °C in January.

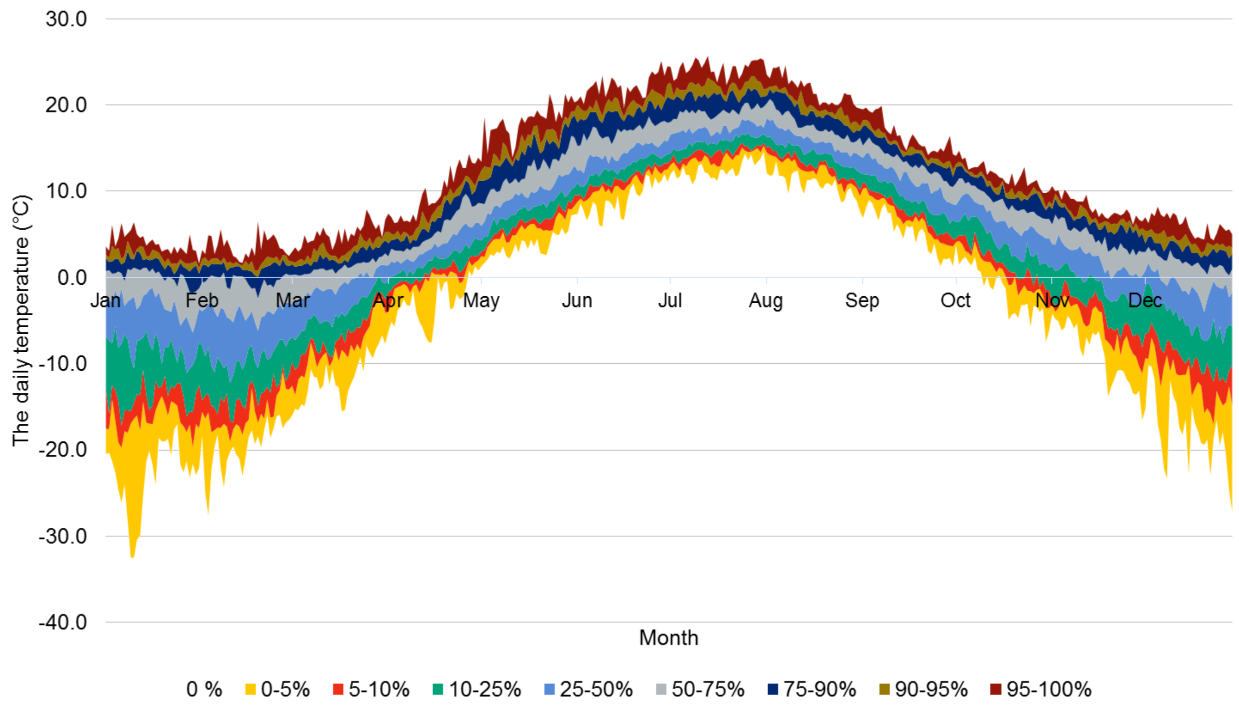

Figure 9: *The daily mean temperature variance of Helsinki within a year in 1962–2012. The corresponding percentiles are presented with different colors in the figure. The data on the figure was acquired from the open data datasets of the Finnish Meteorological Institute (Finnish meteorological Institute 2015).*

The hourly demand profiles are based on the historical temperature data series of Helsinki, Jyväskylä and Oulu from 1962–2012. The temperature time series were acquired from the open data datasets of the Finnish Meteorological Institute (Finnish meteorological Institute 2015). Figure 10 shows the variation in the hourly demand profile during second week of the year according to the modeled correlation between temperature and demand. The figure displays how the minimum, maximum and average temperatures affect the demand profile of southern Finland during the historical period 1962–2012. The peak values of the demand profile are met during cold winter temperatures and minimum values with mild temperatures. The figure shows that the maximum demand occur less frequently than the minimum demand indicating that really cold temperatures are more uncommon than mild temperatures. Each day is clearly recognizable since the electricity demand during the day is higher than during the night. Also, higher demand can be expected during weekdays than during the weekend.

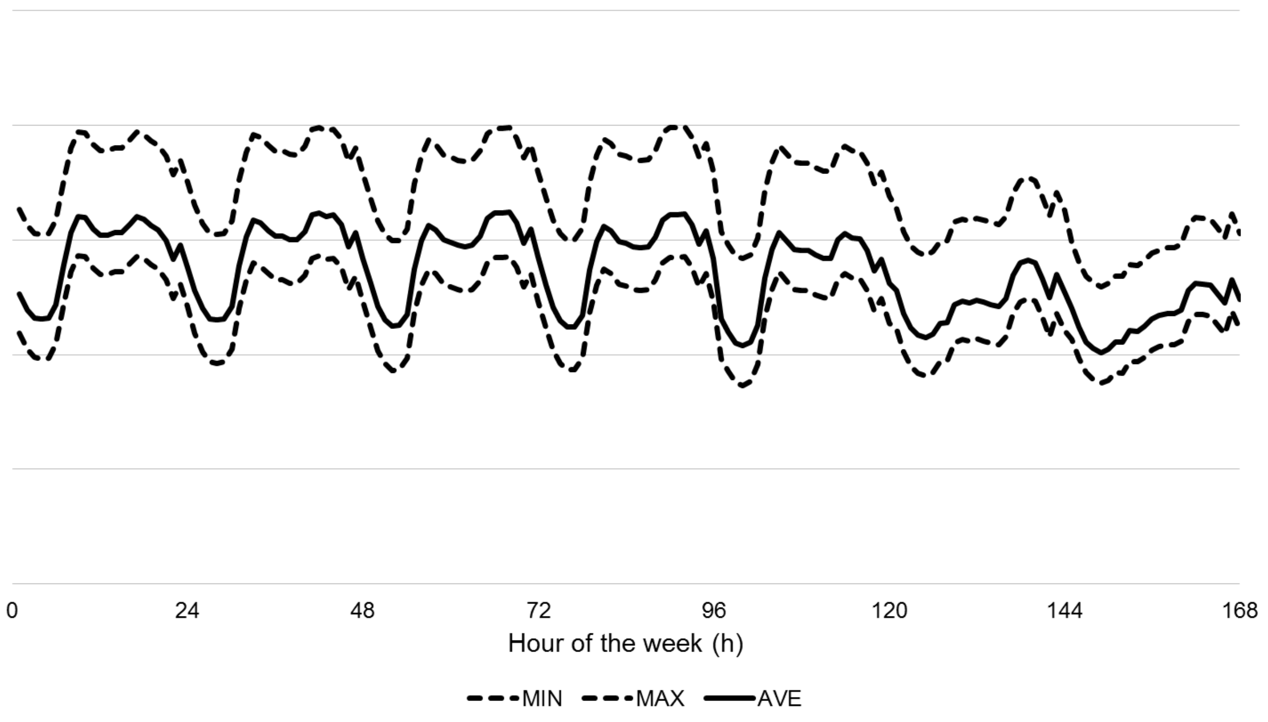

Figure 10: *The variation of hourly demand profiles according to the temperature correlation in Finland within the second week of the year. The temperature data was according to datasets of the Finnish Meteorological Institute (Finnish meteorological Institute 2015). The figure shows the modeled minimum, maximum and average values.*

CHP must run generation related to the district heating was based on the same temperature data as with demand. Must run generation corresponds to the power generation related to the heat production in the combined mode of the CHP power plant. Examples of must run constraints are the need for a certain district or industrial heat demand or process steam. In this study, CHP must run generation related to district heating was only modeled to correlate with the temperature. The modeling was believed to make a notable improvement on the results since CHP production has a significant role in the power system of Finland.

Figure 11 shows the variance of the modeled CHP must run generation in Finland in 1962–2012. The figure illustrates that CHP is modeled to produce more electricity during colder temperatures which can be seen as a higher curve during the winter months. This can be explained by the increased need of district heating which also increases the produced electricity. During the summer season, the CHP must run generation decreases with the lower need for district heating resulting from a warmer season. The CHP must run profile was modeled to reach its maximum generation capacity at -5 °C and the minimum at 20 °C. The limits can be seen as the flat curve in the maximum curve of the winter season and in the minimum curve of the summer season. According to the modeled hourly profiles, the amount of demand side response in the studied power system was not assumed to increase in the future. Also, the correlation between the temperature, demand and CHP must run production was assumed to remain at the same level in the future.

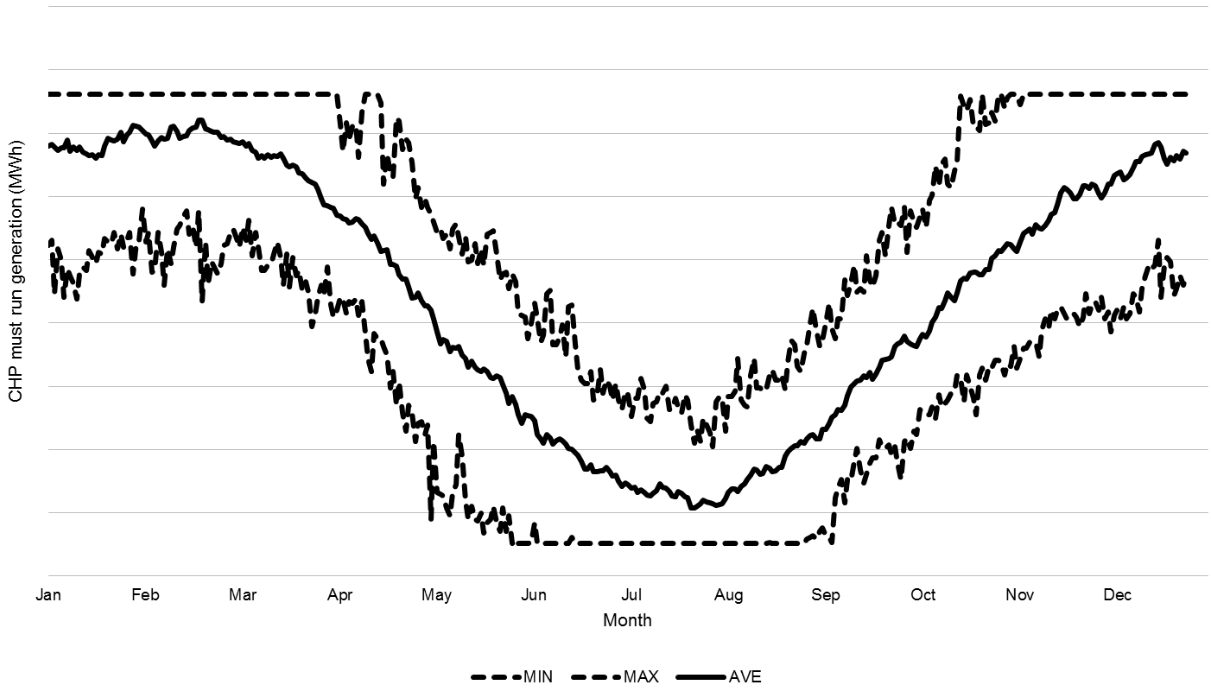

Figure 11: *The variation of the modeled hourly CHP must run profiles related to district heating within a year depending on the temperature in Finland in 1962–2012. The figure shows the modeled minimum, maximum and average modeled CHP must run profiles.*

Hydro inflows were modeled to correlate with the precipitation and **wind power hourly profiles** with wind speed from the time period 1962–2012. Figure 12 and Figure 13 show the modeled variation of wind power production and hydro inflows in Finland respectively. The data on the figures was processed by SINTEF according to reanalysis data (SINTEF 2015). The variation of the wind power production displays that the speed of wind variates significantly throughout the year. Modeling the wind power production with an average profile would ignore the high uncertainty relating to wind power production.

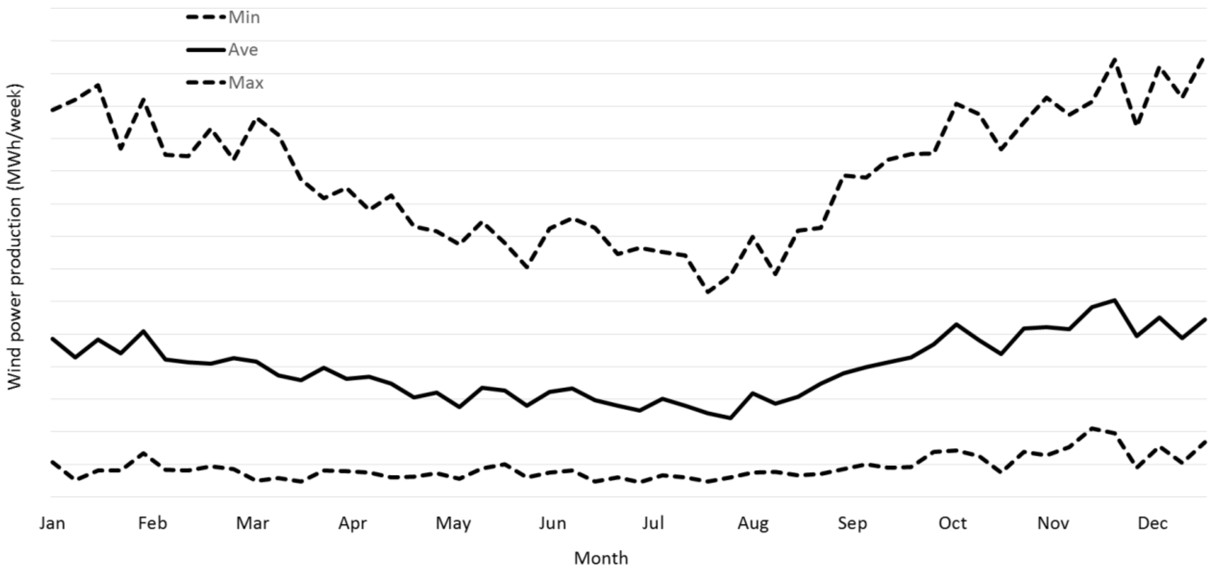

Figure 12: *The variation of the modeled hourly wind power production within a year depending on the wind speed in Finland in 1962–2012. The figure shows the modeled minimum, maximum and average modeled wind power production per week. The data on the figure was processed by SINTEF according to reanalysis data (SINTEF 2015).*

The modeled hydro inflows (Figure 13) show that the amount of hydro inflows can vary greatly depending on the observed weather year and the amount of inflow depends on the season of the year. There is a clear peak in the amount of average inflow during the spring floods, while the rest of the year seems to be quite steady. It can also be seen that the average profile (red) describes the trend quite well, but would not represent the hydro inflows with their representative probabilities.

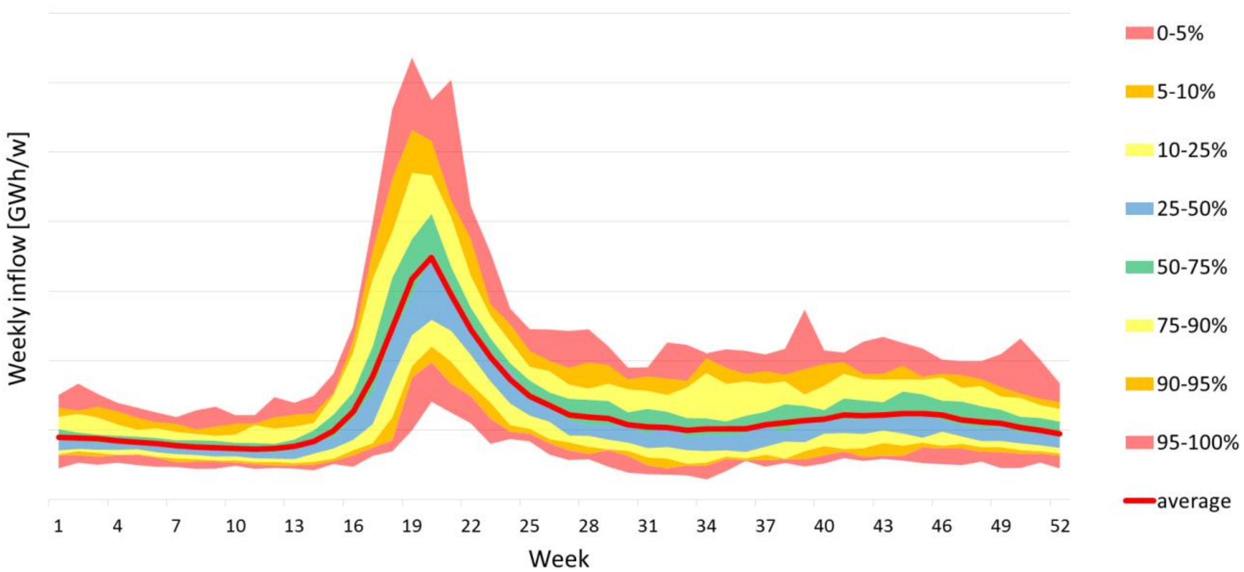

Figure 13: *The variation of the modeled weekly hydro inflow profiles within a year depending on the precipitation of Finland in 1962–2012. The corresponding percentiles are presented in the figure. The data on the figure was acquired from the Finnish Environmental Institute (SYKE 2015).*

5.4 Proposed Power Adequacy Analysis Method

5.4.1 Methodology

The proposed method for assessing power adequacy in a power system is based on a **chronological Monte Carlo Simulation method on an hourly resolution**. As discussed in the sub-section 2.5.1, there seems to be a consensus between the previous studies that a chronological, stochastic method with an hourly resolution produces the most accurate results when appropriate input data is available. Monte Carlo Simulation was chosen for the calculation method, because the modeling of a power system comprises a vast number of unknown parameters with multiple possible states and Monte Carlo simulation can represent the results with their appropriate probabilities.

The parameters which are variated stochastically in the Monte Carlo simulation are weather dependent parameters in addition to plant and interconnector outages as shown in Figure 14. Weather dependent parameters are wind power, hydro inflows, demand and CHP must run production.

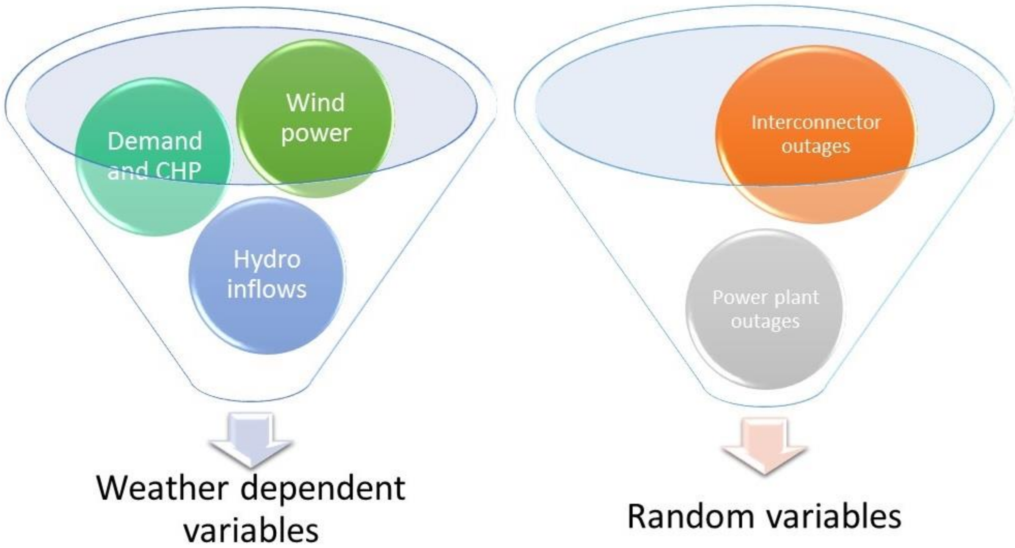

Figure 14: *Weather dependent variables includes demand, CHP must run, wind power and hydro inflows. Random variables comprises power plant outages and interconnector outages. Random variables are generated with the stochastic tool introduced in this study.*

The weather dependent variables comprises 51 weather years. The weather years are based on the historical weather data which included harmonized data from temperature dependent demand, temperature dependent CHP must run related to district heating, wind power production and hydro inflows in the Baltic Sea market area in 1962–2012. This way there are 51 * 8760 possible states for weather dependent parameters which are harmonized and time-synchronized across the whole analyzed power system. Previous studies indicated (sub-section 2.5.1) that time-synchronized, harmonized demand and generation data is necessary for correctly representing the unpredictability of weather in adequacy analysis.

The historical input data of 51 years can be considered to represent different weather conditions well. Pentalateral Energy Forum (2014) used 10 chronological weather years in their study but highlighted that more weather years would be needed in the future. VTT used 35.5 years of weather data in their study which is in line with the argument by Holttinen et al. (2009) that 10–30 years of hourly weather data would be sufficient for a chronological Monte Carlo simulation method. However, VTT (2015, p.10) stated that the longer time series are used the more reliable the results are.

Some previous studies (Pentalateral Energy Forum 2014) have not harmonized hydro inflows with other weather dependent factors due to the lack of appropriate data. This could lead to misleading results, since that kind of a method assumes that the temperature and precipitation do not correlate at all. Harmonization should be used for all parameters, which could be interdependent. The studied power system has a significant amount of hydro power, why the harmonization of all the weather dependent parameters was seen important for the proposed method.

5.4.2 Input Data

The power plant and the interconnector outages were generated with a random sampling method introduced in Section 5.2. In power market simulators, maintenances and outages can be modeled by inserting an hourly availability profile for each separate generating unit or interconnector. A generating unit consists of a single power plant or an aggregation of similar power plants. Each relevant unit was given an individual stochastic availability profile. Power plants over 100 MW in Finland, Swedish Nuclear power and interconnectors of Finland and Sweden were considered relevant in this study. The commercial capacity limit of the actual transmission lines was used as the capacity of the interconnectors. The internal transmission network is taken into account according to how it affects the transmission capacity between market areas.

In this thesis, two types of faults are only taken into consideration: power plant faults and faults related to interconnectors between bidding areas. The interconnectors include actual power lines between bidding areas and equipment which affect the transmission of those lines. Therefore, some faults, which occur in transmission lines inside bidding areas, are not examined. Faults occurring in distribution networks are also outside the scope of this study.

There were a total of 153 availability profile years generated for both relevant power plants and interconnectors. An availability profile year consists of a set of hourly availability profiles for each relevant unit. A Monte Carlo simulation case was formed by pairing each weather year with a random power plant profile year and a separately randomized interconnector profile year. There were a total of 459 simulation cases as shown in Figure 15. This was done by sampling each historical weather year with nine randomly chosen availability profile years, which increased the variance in the relationship between the historical weather year and randomly sampled availability profile year. The power plant availability profile year and the interconnector availability profile year were separately randomized to variate the relationship between interconnector outages and the power plant outages. As a result, each weather year is run nine times and each availability profile year three times, but each case combines the profiles differently.

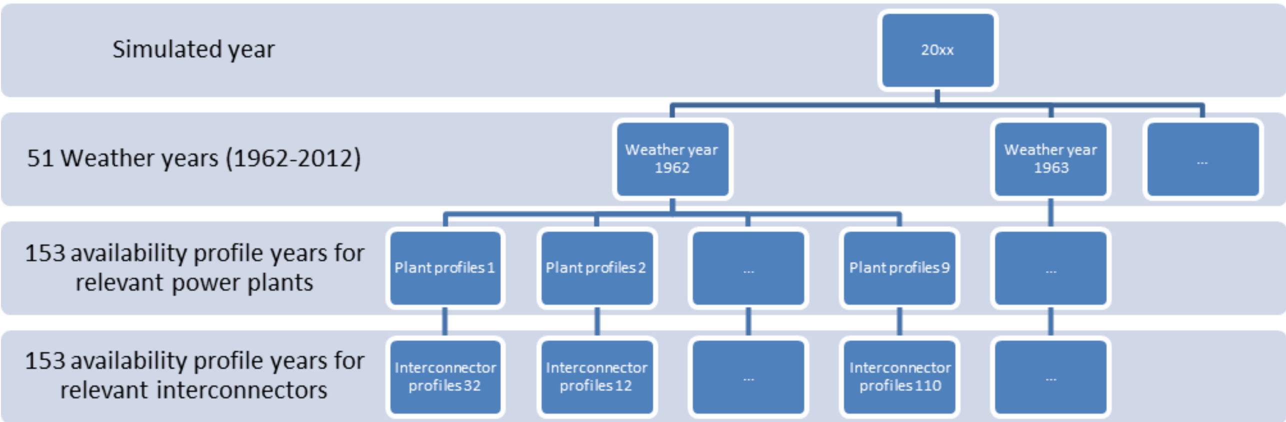

Figure 15: *The methodology of the proposed method. Each model run comprises a historical weather year coupled with a sampled power plant availability profile year and a separately sampled interconnector availability profile year.*

For example, A Monte Carlo case can consist of a simulated year 2014 with the weather year 1962, a power plant profile year 1 and an interconnector profile year 32. This means that the nominal capacities of each power plant and interconnector are set to describe the year 2014. Also, other variables of the power system like the total demand consumed, fuel prices etc. are set to describe the historical year 2014. However, the weather conditions and occurring faults are variated according to the weather year and the availability profile years. A weather year 1962 can be thought as analyzing the year 2014 with the weather conditions that occurred in 1962; the temperature, the precipitation levels and the wind speed. The randomly sampled power plant availability profiles and the interconnector availability profiles would describe the situation in 2014 if all the forced outages occurred during random times and lasted for random periods. The different combinations can be simulated with a power market simulator.

In this methodology, it is assumed that the weather dependent parameters do not correlate with the outages of units. The assumption means that the faults of a power plant are not influenced by the temperature, the wind speed or the precipitation. With the exception of fierce storms inducing problems in overhead lines, the assumptions are considered quite safe. Also, each individual fault is considered as an independent event. It is assumed that an occurring fault in a power plant does not change the probability of an occurring fault in the same or another power plant or an interconnector.

5.4.3 Output

Loss of Load Expectancy, **Energy Not Served** and **remaining capacity** are monitored as output. Each index provides a different view on the adequacy level of the power system, which can be combined to an overall interpretation. As stated in sub-section 2.5.1, most of the stochastic, chronological methods output several adequacy indices. North American Electric Reliability Corporation (2014, p. 28) highlighted that adequacy indices, that can account for variable and stochastic nature, are necessary to obtain an accurate probabilistic assessment of adequacy.

Effective load carrying capacity (ELCC) is used more with approximate methods, why it is not monitored in the proposed method. ELCC index was not seen to improve the results of the method in addition to the other monitored indices. The calculation methods of ELCC were also found problematic in Section 2.2, as LOLE, ENS and remaining capacity indices can be quite ambiguously calculated.

Pentalateral Energy Forum (2014) combined each weather year with an individual availability profile year. In this study, the simulated sample size was increased by combining multiple availability profile years per each weather year. The method leads to a better possibility to meet the central-limit theorem of a large enough sample that represents the system well enough. The effect of the additional samples on the certainty of the result is studied in sub-section 7.2.2.

Uncertainty in the results must be tolerated when performing a Monte Carlo analysis. The accuracy or the error marginal of the Monte Carlo simulations can be approximated with a confidence interval approach explained by Byrne (2013). According to the approach, the integer number of model runs required (n) can be derived with the eq. (7),

$$n = \left(\frac{z_{\alpha/2}}{w} CV\right)^2, \text{ where} \tag{7}$$

CV is the coefficient of variation, $z_{\alpha/2}$ is the confidence level and w is the desired confidence interval width. The generally used confidence level is 95 %, the value of which is 1.96. The desired confidence interval width explains how close the calculated mean of the sample is with the true prediction. CV is the ratio between the variation of the sample and the average of the sample.

The eq. (7) can be used to derive the values in Table 6, which shows the minimum number of simulations required for the desired confidence interval width assuming 95 % confidence level. (Byrne 2013) For example, assuming a sample variation of 1.0 and average of 2.0, then, the coefficient of variation equals 0.5. If at least 384 simulations are run, the true prediction of the model is within 5% of the mean of the sample.

Table 6: *The number of simulation runs (n) as a function of coefficient of variation (CV) and the confidence interval width w*

		CV				
		0.5	**1**	**2**	**3**	**4**
w	**0.01**	9604	38416	153664	345744	614656
	0.02	2401	9604	38416	86436	153664
	0.05	384	1537	6147	13830	24586
	0.1	96	384	1537	3457	6147
	0.15	43	171	683	1537	2732

The eq. (7) can be derived into a form which calculates the confidence interval width (w) as a function of number of simulation runs as seen in eq. (8):

$$w = \frac{z_{\alpha/2}}{\sqrt{n}} CV \tag{8}$$

The equation indicates that a larger coefficient of variation increases the confidence interval width. This can be explained by that the confidence interval width is directly proportional to the average of the model and indirectly proportional to the variation of the model.

According to Byrne (2013), two assumptions needs to be met when calculating confidence intervals. Firstly, the assigning of random variables must be truly random, so some numbers cannot be more likely than others. Secondly, each model run must be statistically independent of the other runs. One run cannot affect the behavior of other runs and they must come from the same distribution. The proposed method fulfills both criteria.

6 Simulation Cases Applied to the Baltic Sea Market Area

This chapter describes the simulation case studies that were performed in this thesis and the modeling assumptions used. The chapter can be divided into three parts. The first part describes the studied power system. The second and third part explain the conducted sensitivity analyses and case studies respectively.

6.1 Geographical perimeter of the Simulation Cases

The geographical perimeter covered in this study was limited to the ENTSO-E countries in the Baltic Sea market area, including also the Netherlands. The modeled perimeter is depicted in Figure 16. In all simulations, transmission capacities between the Baltic Sea market area countries and other neighboring countries (e.g. Finland-Russia, Germany-France, Norway-UK) were set to zero, with the exception of modeling the interconnector between Belarus and Lithuania.

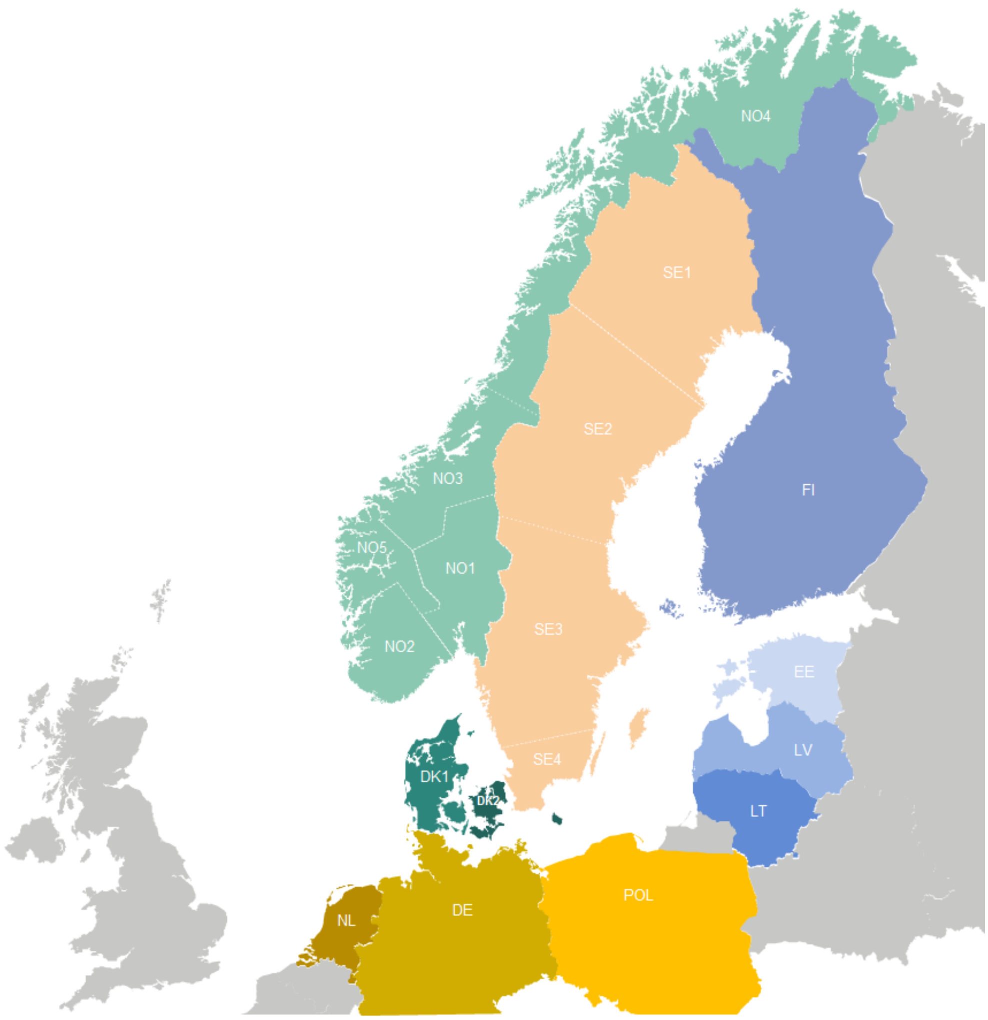

Figure 16: *The geographical perimeter which was used in the simulation cases of this thesis.*

6.2 Sensitivity Analysis on Simulation Parameters

This section describes two different sensitivity analysis studies. The section examines the effect of different simulation modules in the BID version 3.1.3 and the convergence of the results.

6.2.1 Simulation Program Run Settings

BID 3.1.3 contains different simulation run settings that can be used to calculate the adequacy indices. The purpose of this section was to study, which run settings affect the output accuracy relating to the adequacy indices and which setting produces the optimal trade-off between simulation results in detail and calculation time. However, the calculation time was to be reasonable, as in an overnight calculation time is still reasonable and everything beyond that is questionable. The results of this sensitivity analysis is shown in Sub-section 7.1.1.

The goal of this sensitivity analysis was to test if the Capacity Margin module produces reliable results when the Detailed Simulation module results of the BID 3.1.3 are considered as the best estimate. Both modules can be used to monitor the adequacy indices, but the optimization perspective is different. The Detailed Simulation module optimizes the energy use of the system as the Capacity Margin module is a capacity-only method. The Detailed Simulation module takes both the shortage of capacity and the shortage of energy into account, whereas the Capacity Margin module focuses on the shortage of capacity.

The results of the calculation time are also subject to the hardware equipment. All the simulations of this thesis were run with a six-core AMD Opteron Processor 8431, all of which included four 2.4 GHz processors. The computer operating system was 64-bit Windows Server 2008 R2 Enterprise. The computer had 72.0 GB of installed RAM memory.

The sensitivity analysis on the simulation program run settings was performed with a 2014 dataset in the Baltic Sea market area. Two cores were used in calculation for each run. The use of two cores should show lower simulation time with settings which can take advantage of parallel calculation resources.

Table 7 presents the four different simulation runs performed in this sensitivity analysis. The analysis studied the effects of the different run settings of BID 3.1.3 on the power adequacy indices in Finland. Runs A and B were simulated with the program's Detailed Simulation module, whereas runs C and

D with the Capacity Margin module. The monitored power adequacy indices were loss-of-load expectancy, energy not served and minimum remaining capacity. In addition, the simulation time was monitored in order to do qualitative analysis on the applicability of a faster but more approximate simulation.

Table 7: *Four different BID 3.1.3 simulation run settings simulated in the sensitivity analysis*

Run	Simulation module	Sequential / Non-Sequential	Number of cases run
Run A	Detailed Simulation	Sequential	51
Run B	Detailed Simulation	Non-Sequential	51
Run C	Capacity Margin	Non-Sequential	51
Run D	Capacity Margin	Non-Sequential	459

The Detailed Simulation module can be run with two different settings in BID 3.1.3: a Sequential or a Non-Sequential setting. Run A was simulated with 51 cases with a Sequential run setting and run B with 51 cases with Non-Sequential run setting. The cases comprised 51 weather years where each case was combined with a different availability profile year. Sequential Simulation uses the hydro reservoir filling levels of a previous weather year as the starting point of the subsequent weather year. This means that each weather year must be simulated in the correct order. Sequential Simulation can thereby monitor the effect of a multi-year lasting dry season on power adequacy indices, whereas the Non-Sequential cannot. Non-Sequential Simulation uses the same initial starting point for each case and thereby simulates each weather year independently.

Run C simulated the same 51 cases with the Capacity Margin module. Run D simulated 459 simulations in total with the Capacity Margin module. 459 simulations were composed of 51 weather years with each mixed with nine different availability profile years for power plants and interconnectors.

At first, in the runs A, B and C, very low values for the adequacy indices were observed. As previous research indicated (Section 2.2), the traditional adequacy indices are not meaningful in a power system where the probability of a power deficit is very low. Figure 17 shows the duration curve of the remaining capacity of each hour of the year in blue in an example Detailed Simulation case in 2014 with the full generation capacity. It can be seen that even the minimum remaining capacity is positive each hour of the year which would result in a meaningless comparison of the LOLE and ENS indices.

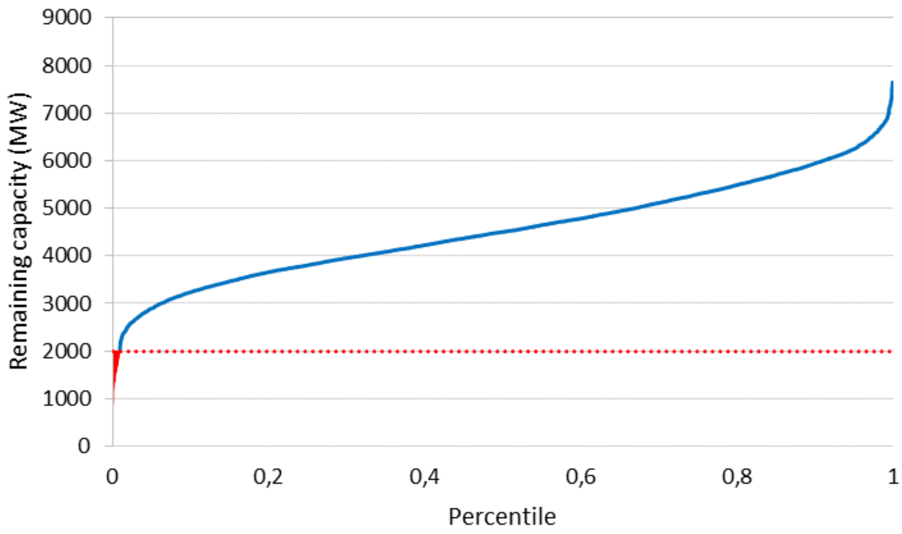

Figure 17: *The modified remaining capacity of each hour of the year in an example simulation run. By removing 2000 MW from the generation capacity, the x-axis moves upward and non-zero adequacy indices can be observed. The red area on the left shows the hours during a loss-of-load would occur after decreasing generation capacity.*

To avoid the problem, the total generation capacity of Finland was decreased by 2000 MW in this sensitivity analysis. The subtraction was made from the generation capacity from each hour of the year so that the effect of the subtraction on the power system adequacy would be exactly the same throughout the year. The same net effect could have been produced by increasing demand by 2000 MW each hour of the year. However, it was easier to implement the effect by subtracting generation capacity with the used power market simulator.

Meaningful values for the LOLE and ENS indices were recorded with the modified dataset. The induced loss-of-load is shown as a red area in Figure 17. The generation capacity of Finland was only decreased in the simulation program run setting sensitivity analysis. The other sensitivity analysis and case studies introduced later in this thesis were performed with the original dataset.

6.2.2 Convergence of the Results of the Power Market Simulator

The convergence depicts how many simulation years should be simulated to produce a best estimate that corresponds to the modeled system well enough. This is based on the theory of the Monte Carlo simulation explained in Section 5.1. Monte Carlo Simulation relies on generating a number of states that represent the whole set well enough.

In this study, 459 Monte Carlo simulations were chosen for the proposed method. However, previous studies that were presented in Section 2.5, used substantially less case simulations. In the studies, the chosen number of simulations were not statistically proven, why the convergence of the results was tested in this thesis. The aim of this study was to validate that 459 simulations are enough and to test if even smaller amount of simulations would lead to sufficient accuracy.

The convergence was tested by running the Capacity Margin module first with 459 simulations. The simulations consisted of nine collections of 51 weather years. In order to preserve the correct probabilities of the representative weather years, the simulations were run with the multiples of 51 so that each weather years has an equal probability of occurrence. Each run can be considered independent. If 459 Monte Carlo cases are observed to be inadequate, more cases are run until the mean converges.

The convergence is tested against two approaches which were introduced in Section 5.1. According to the first approach, the results convergent when additional model runs do not change the mean of the model estimation notably. The second approach was based on the confidence interval of the results. The results of the case study are shown in Section 7.1.2.

6.3 Application to the Baltic Sea Market Area

This sub-section describes two applications of the proposed method to the Baltic Sea Market Area. The first study analyzes the development of the adequacy level of Finland in 2012–2023. In the second study, the proposed method is implemented to analyze how a grid investment in the cross-border interconnector capacity affects the adequacy level of Finland.

6.3.1 Case Study 2012–2023

The proposed adequacy analysis method was applied to assess the development of the adequacy level of Finland in 2012–2023. The adequacy level was analyzed in the past years 2012 and 2014, in addition to the future years 2017 and 2023. These years were chosen to represent the most significant capacity changes in the power system.

The input values corresponding to the simulated year were based on predefined assumptions, which were not developed or evaluated during this study. Instead, the assumptions were utilized to test how the proposed methodology can be applied in adequacy analysis of real power systems. In general, the assumptions followed the recent trend in the Baltic Sea market area: the share of wind power of total generation capacity was expected to increase and the share of thermal power was expected to decrease. The peak load reserve capacities of Finland and Sweden were included in the case study years

2012, 2014 and 2017 according to the current public market information. No peak load reserve was assumed for the case study year 2023 since there was no existing decision on the peak load reserve capacity in 2023 at the time of the study.

Each year was run with the proposed method of 459 Monte Carlo simulations. The average and the duration curve of the power adequacy indices were observed and compared between the different simulated years. The averages should show the main trend of the power adequacy development, whereas the duration curves show the shape of the variation of the results of the simulated Monte Carlo cases. The duration curve shows the representative probabilities for possible outcomes. The results of this convergence analysis are shown in Section 7.2.1.

6.3.2 Case Study - Interconnector Analysis

The proposed method was implemented to analyze how a reinforcement of a cross-border interconnector between Finland and Sweden would affect the adequacy level of Finland. The analysis was performed by simulating the year 2023 with the ENTSO-E's Cost Benefit Analysis of Grid Development Projects method called PINT. The PINT method stands for Put IN one at the Time which considers each new network investment one at a time and evaluates the system with and without the examined network reinforcement (ENTSO-E 2013, p. 28).

The reference scenario corresponded to the assumptions explained in Section 6.2.1 for the case study year 2023. The cross-border capacity between Finland and Swedish price area SE1 was assumed at 1200 MW in 2023. In the PINT scenario, the interconnector capacity from the north of Finland to the north of Sweden was increased by 800 MW to a total of 2000 MW. Other input values were the same in both scenarios. The effect of the grid investment on the adequacy indices was monitored and compared. The results of the case study are shown in Section 7.2.2.

7 Results of the Simulation Cases

This chapter presents the results of the sensitivity studies and case studies in this thesis. The first section shows the results of the sensitivity analyses on the simulation program run settings and the convergence of the results. The second section illustrates the results of two exemplary applications of the proposed method.

7.1 Sensitivity analysis on the Simulation Parameters

7.1.1 Simulation Program Run Settings

The sensitivity analysis on the simulation program run settings showed that the faster and more approximate Capacity Margin module is applicable to analyzing the adequacy indices of the observed power system reliably. Table 8 shows the simulation time, LOLE, ENS and the minimum remaining capacity of four simulation runs A, B, C and D. The minimum remaining capacity corresponds to the remaining capacity of a single hour when the adequacy level is the lowest during the case year.

Table 8: *The effect of simulation program run settings on LOLE, ENS, min remaining capacity and simulation time with presentative 2014 dataset where 2000 MW was subtracted from the Finnish generating capacity*

Simulation run	Cases	Time (h)	LOLE -2000MW (h)	ENS -2000MW (MWh)	Min remaining capacity -2000MW (MW)
Run A	51	26h 42min	55.8	20192	-1816
Run B	51	16h 46min	55.8	20192	-1816
Run C	51	56 min	55.7	19965	-1815
Run D	459	8h 12min	55.4	18909	-2833

The difference between the LOLE and ENS columns is very marginal when looking at the runs A, B and C which all were run with 51 simulation cases. The Detailed Simulation module runs A and B produced exactly the same results. Also, the results of the Capacity Margin module run C were surprisingly close to the other runs. If the results of the Detailed Simulation are considered as the best estimate for the model, the results of the Capacity Margin model LOLE and ENS correspond to an error of 0.2 % and 1.1 % respectively.

The low difference between the results of the runs indicates that taking energy optimizing into account does not affect the adequacy indices notably in the simulated power system. The result was somewhat unexpected that the faster Capacity Margin module can replicate the results of the runs A and B which use energy optimization with such accuracy. However, this can be explained that the studied power system lacked units with a small energy storage capability compared with its capacity. These units can efficiently respond to the capacity problems in the short term but could run out of energy during a longer period of time, which the Capacity Margin module does not take into account. For example, demand side response, hydro power plants with small reservoir and electricity storages are typical units like this.

The sequential simulation does not affect the adequacy results compared with the non-sequential simulation according to the results. A low reservoir level resulting from a multiple continuous dry years should affect the availability of the hydro power plants. However, the relationship was not modeled in the input data in this study, which explains why difference between the runs A and B could not be seen in the results.

The calculation time can be substantially reduced by running the Capacity Margin module. Run C was simulated in less than an hour as the run A and the run B lasted for more than 16 and 26 hours respectively. The result was expected because the Capacity Margin module does not utilize energy optimization. Sequential Simulation can only use a computer processor core for the calculation as the Non-Sequential and the Capacity Margin module can use multiple cores for parallel calculation, which results in lower simulation time. This explains the simulation time difference between the runs A and B.

The duration curve of the LOLE for each run (Figure 18) confirms that the faster Capacity Margin module can be used to estimate the adequacy indices well enough. It can be seen that the green curve of the run C is different from the blue curve of the run B at certain points. However, the difference is quite small in comparison with the overall results. The duration curve of the runs A and B are alike which shows that there was not any noticeable difference between the results of the run A and B.

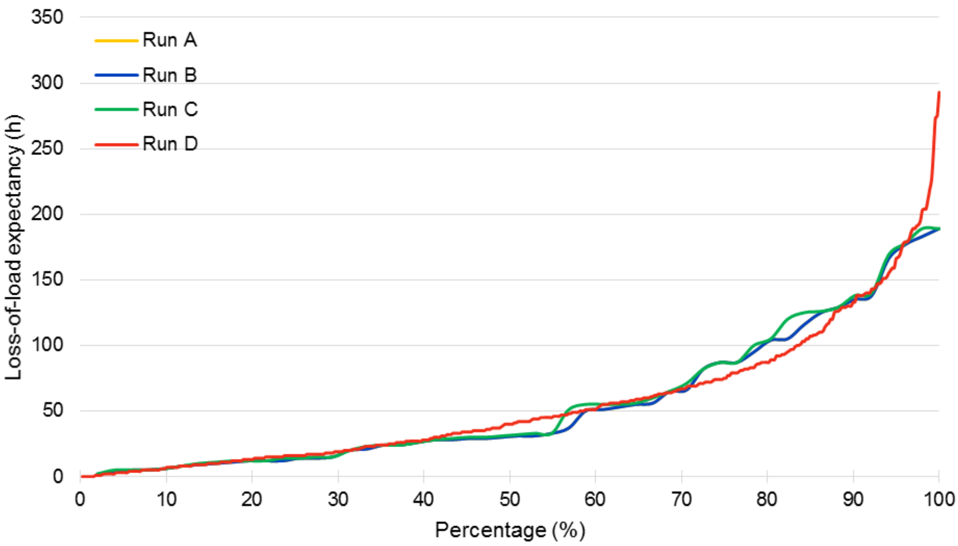

Figure 18: *The duration curve of the LOLE index of the runs A, B, C and D.*

The red curve shows the results of the run D which was simulated using 459 Monte Carlo simulations with the Capacity Margin module. According to the duration curve of the LOLE index, the run C seems like a quite good approximation of the run D. There is only a significant difference in two percent of the most severe cases.

The duration curves of the energy not served (Figure 19) and the minimum remaining capacity (Figure 20) illustrates a somewhat different conclusion. The duration curve of the ENS of the run C is a good approximation in comparison with the run D during the first 73 % of the results. On the other hand, the run C would indicate higher ENS for the cases between 73–93 percentiles and, on the other hand, lower ENS for the cases over the 93th percentile than the run D. The duration curve of the minimum remaining capacity of the case C would indicate lower remaining capacity at each percentile in comparison with the run D.

The finding addresses that multiple adequacy indices should be used when analyzing the results since the indices show different characteristics of the system. The example shows that the different indices might not always show similar signals and using a single index could lead to misleading results.

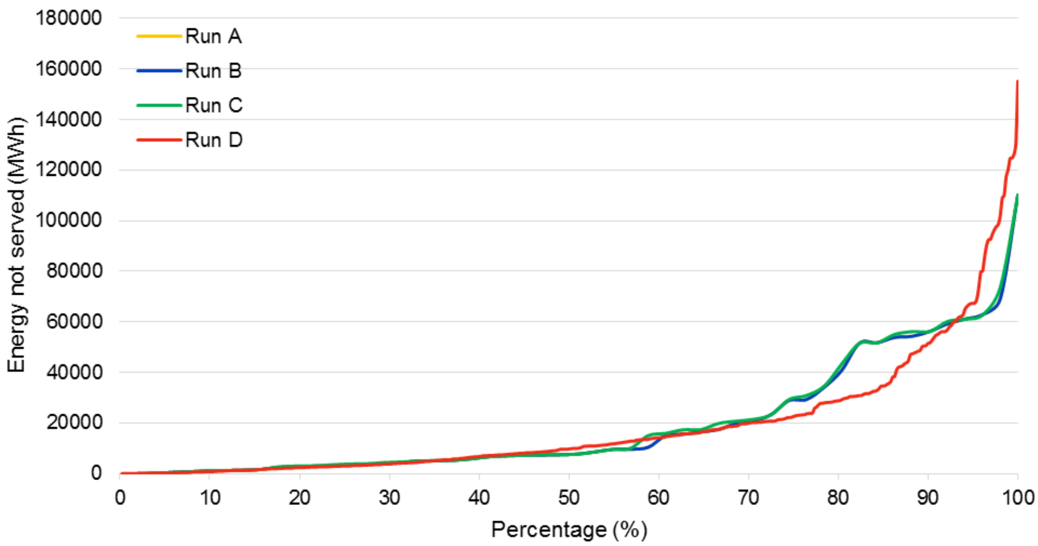

Figure 19: *The duration curve of the ENS index of the runs A, B, C and D.*

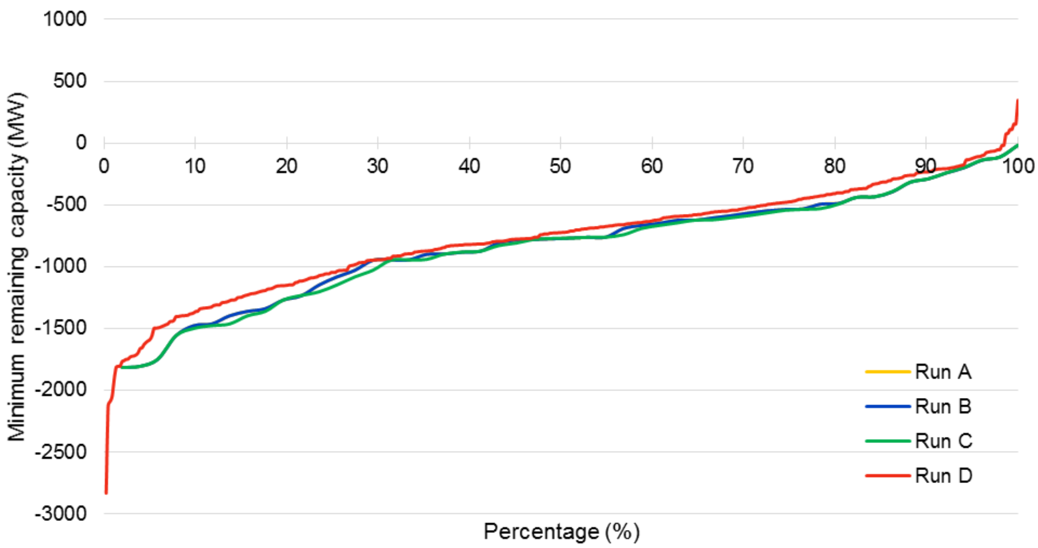

Figure 20: *The duration curve of the minimum remaining capacity index of the runs A, B, C and D.*

The simulation time of the run D was 8.2 hours. This means that each additional simulation run of 51 weather years took about 55 minutes. It shows that the simulation time of running a more extensive Monte Carlo simulation of 459 cases with the Capacity Margin module is still reasonable and the time is less than the time running a Detailed Simulation of 51 Monte Carlo cases. The duration curves show that the more extensive run D produces higher variation in results which can be seen in the tails of the curve at both ends. Higher amount of Monte Carlo simulations runs up to more situations that are more extreme but more unlikely at the same time. The effect of running more Monte Carlo simulations on the uncertainty of the results is covered more in the next sub-section.

7.1.2 Convergence of the Results of the Power Market Simulator

According to the first approach, the model results converge, when the mean of the model does not change notably after additional model runs. Figure 21 and Figure 22 show the results of the LOLE and the ENS indices of this study respectively. Each point on the red curve depicts the average of the results of nine individual runs which are called hereafter with letters A–I in order. A single run consists of 51 Monte Carlo cases. The blue curve shows the cumulative average of the simulation runs which depicts the best estimate for the model as more Monte Carlo simulations are run. For example, the third point from the left refers to the average of the runs A–C which are shown by the red curve.

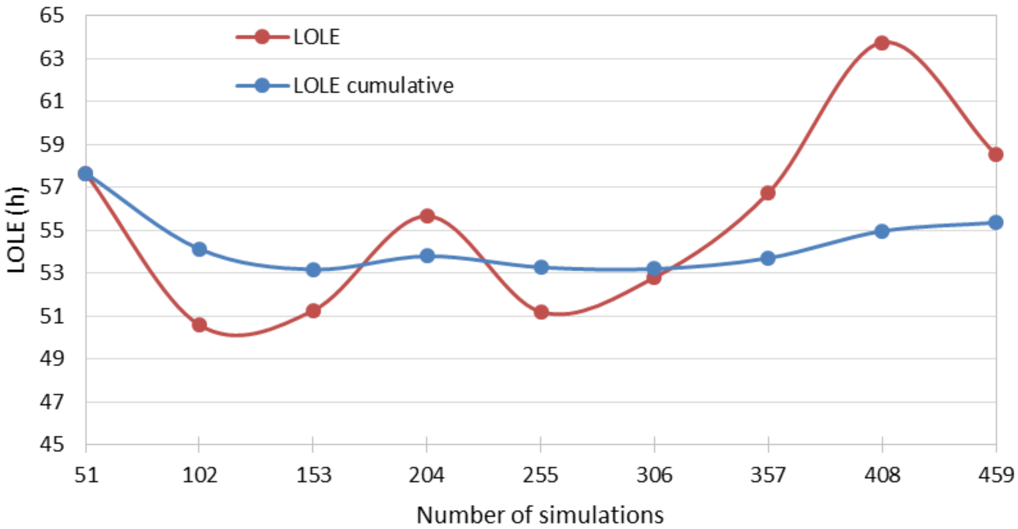

Figure 21: *The LOLE values of the simulation runs A–I. Each simulation run corresponds to 51 Monte Carlo simulations. The red curve shows the average of each individual run. The blue curve shows the cumulative average of the model as more Monte Carlo simulations are run.*

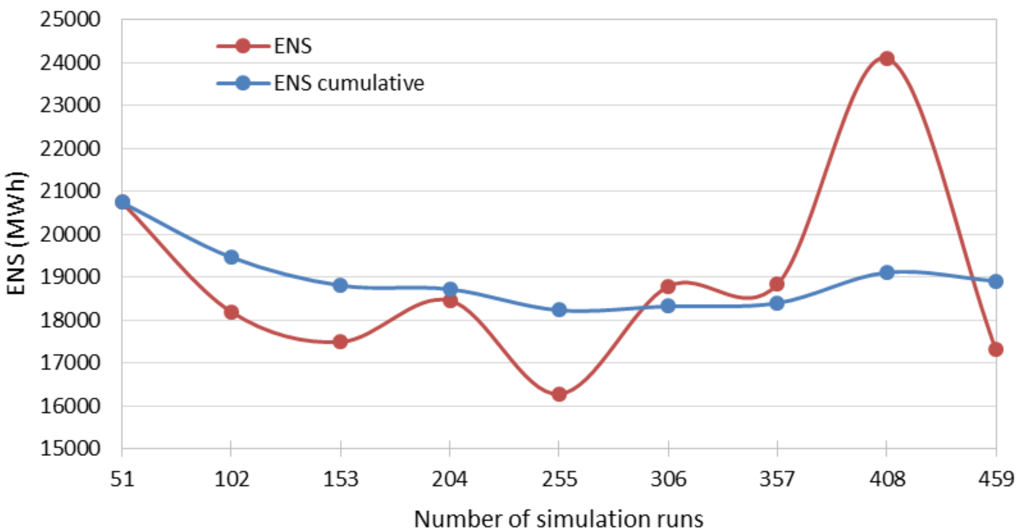

Figure 22: *The ENS values of the simulation runs A–I. Each simulation run corresponds to 51 Monte Carlo simulations. The red curve shows the average of each individual run. The blue curve shows the cumulative average of the model as more Monte Carlo simulations are run.*

According to the curves, the best estimate of the model seems to converge well before the nine runs which would verify the hypothesis that 459 Monte Carlo simulations produces a representative sample of the set and more simulations are not necessary. The best estimate for the model LOLE and ENS were 56 h/year and 19 000 MWh/year respectively after nine runs. Between 102–459 simulations, the average of the LOLE variates between 53–55 h/year, whereas the ENS variates between 18 200–19 100 MWh/year. They are within 5 % and 3.5 % of the best estimate of the model respectively.

In my opinion, the approach does not produce enough evidence to indicate more precisely how many simulations would be sufficient. Looking at the red curve, there is some variance between the individual runs. The lowest LOLE of 51 h/year is observed at run B and the highest LOLE of 64 h/year at run H. As stated in Section 5.1, the approach usually needs thousands or tens of thousands of simulations for unambiguous results.

The second approach evaluated the convergence from a confidence interval perspective. According to eq. (8, p. 45), the confidence interval width depends on the coefficient of variation (CV) of the sample results. The coefficient of variations for the LOLE and the ENS indices were calculated according to the average and the variation of the sample results. Then, the eq. (8) was used to derive the confidence interval widths in Table 9. Multiples of 51 were used for the number of simulation runs, because this way each one of the 51 weather years has an equal probability of occurring.

Table 9: *The confidence interval width (w) as a function of coefficient of variation (CV) and the number of simulation runs (n)*

		w (%)	
		LOLE (CV = 0.9)	**ENS (CV = 1.3)**
n	**612**	7.5	10.4
	561	7.8	10.9
	510	8.2	11.4
	459	8.7	12.0
	408	9.2	12.8
	357	9.8	13.6
	306	11	14.7
	255	12	16.2
	204	13	18.1
	153	15	20.9
	102	18	25.5
	51	26	36.1

According to the table, the confidence interval width of the results improves clearly when more than 51 simulations are run. With 459 Monte Carlo simulations, the confidence interval width can be decreased to about a third compared with 51 simulations. This is a substantial improvement considering that the simulation time of 459 Monte Carlo cases was considered approvable. However, simulation of over 459 cases did not increase the certainty enough to be sensible. The simulation time of each 51 simulations was somewhat less than an hour, but its effect on the confidence interval width would only be about half a percent when simulating more than 459 cases in this case.

Table 10 illustrates that Byrne's criteria on the confidence intervals stand with the results of the simulated power system. The table shows the separate average of the LOLE of each run A–I where each run corresponded to 51 Monte Carlo cases. The difference between the average of the run and the best estimate for the model in percentage for the LOLE and the ENS indices are presented. It was assumed that the average of 459 simulations produces the best estimate for the model.

Table 10: *The comparison of the run results and Byrne's theory on confidence intervals*

Run	|ΔLOLE (%)|	|ΔENS (%)|
A	4.2	9.7
B	8.6	3.8
C	7.4	7.5
D	0.56	2.4
E	7.5	14
F	4.6	0.66
G	2.5	0.38
H	15	28
I	5.7	8.5

According to Byrne's theory, the confidence interval width of the sample results is 26 % when calculating LOLE values with 51 Monte Carlo simulations. The representative confidence interval width of the sample results is 36 % for ENS. The results of this study seem to agree with the theory. The maximum differences of 15 % and 28 % were observed at run H respectively for LOLE and ENS, which satisfies the theoretical value of the confidence interval width.

In conclusion, the convergence study confirmed that simulating 459 Monte Carlo cases produces results that convergent with an acceptable uncertainty. In the convergence study, 459 Monte Carlo cases produced a certainty of 7.8 % and 10 % for ENS and LOLE values respectively. Therefore, 459 Monte Carlo cases were applied also in the following case studies.

7.2 Application to the Baltic Sea Market Area

7.2.1 Case Study 2012–2023

Table 11 presents the best estimates for LOLE, ENS and minimum remaining capacity of the simulated years for Finland. The estimates for LOLE and ENS include a confidence interval width with a 95 % certainty. The minimum remaining capacity is presented with the results of a simulated median year and a cold year once in 10 years which corresponds to the 90th percentile of the sample in severity. Cold year once in 10 years is later referred as a cold year in this study. The minimum remaining capacity corresponds to the remaining capacity of a single hour when the adequacy level is the lowest during the case year. An occurring load loss in this study means that the day-ahead market solution could not be established. The situation could be resolved by the reserve markets or other market dynamics which are not taken into account in the model (THEMA Consulting Group 2015).

Table 11: *The simulation results of the case studies 2012–2023 with a 95 % confidence interval*

			Minimum remaining capacity (MW)	
Simulation year	LOLE (h)	ENS (MWh)	Median year	Cold year once in 10 years
2012	0.01 ± 0.14	1.4 ± 29	1400	890
2014	0.07 ± 0.09	15 ± 24	990	490
2017	1.8 ± 0.54	490 ± 220	360	-290
2023	5.3 ± 1.1	1800 ± 550	90	-680

Year by year, the probability of an occurring curtailment increases, as available thermal generation capacity is expected to decrease based on the input data described in Section 6.3.1. The trend can be seen in Figure 23 and in Figure 24. Curtailment was very unlikely in 2012 and 2014, which can be seen as very low LOLE and ENS values. Also, the minimum remaining capacity index shows a clearly positive marginal.

In 2017, the average of the loss-of-load expectancy was 1.8 h/year, whereas LOLE of 5.3 h/year was observed in 2023. As discussed in Section 2.3, different European countries have defined an allowed level of loss-of-load expectancy of 3–8 h/year. In 2012, 2014 and 2017, the simulated LOLE would still be under the allowable level in each country, however, in 2023, the simulated adequacy level would only satisfy the adequacy criteria in one of the studied countries.

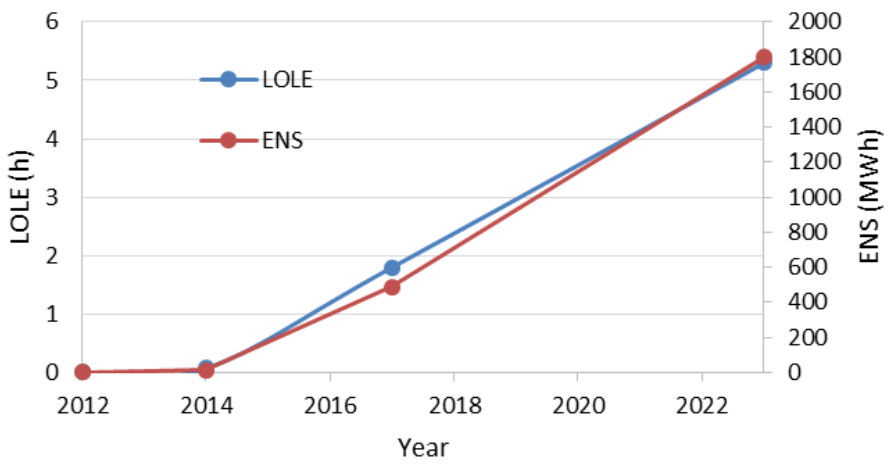

Figure 23: *The development of estimated LOLE and ENS in Finland during simulated years 2012–2023.*

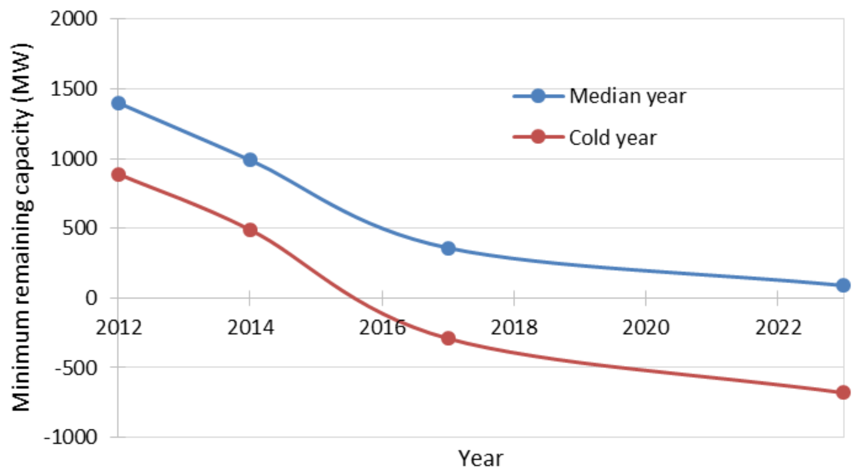

Figure 24: *The development of estimated remaining capacity of Finland during simulated years 2012–2023.*

The simulated averages of the ENS index verify the same trend. By 2017 the best estimate for the energy not served increased to 490 MWh and by 2023 the estimated value of ENS more than tripled to 1800 MWh. According to Fingrid Oyj (2016e), the amount of energy not served was 127 MWh which resulted from occurring faults in transmission lines owned by Fingrid in 2015. The value is not directly comparable with the ENS index calculated in this study since this study measures curtailment in the day-ahead market, not actual undelivered energy, as described in Section 1.3. However, it serves as a reference on the magnitude.

According to the results, the minimum remaining capacity decreases yearly. In 2012 and in 2014, the minimum remaining capacity of a median and a cold year once in ten years is well on the positive side. Under a median year in 2017 and 2023, the minimum remaining capacity is still positive by 360 MW and 90 MW respectively. Curtailment of 290 MW and 680 MW would be expected to occur under a cold year once in ten years in 2017 and 2023 respectively. Curtailment of 290 MW corresponds to about 2 % of the expected peak demand of Finland in 2015, as 680 MW corresponds to about 4.5 percent.

Figure 25 shows the trend of the duration curve of the LOLE index during the simulated years 2012–2023. During each of the simulated year, the most probable outcome was zero loss-of-load hours. However, the rising tails of the curves 2017 and 2023 indicate that loss-of-load is expected to occur more frequently during the later years, as decreased thermal capacity is expected.

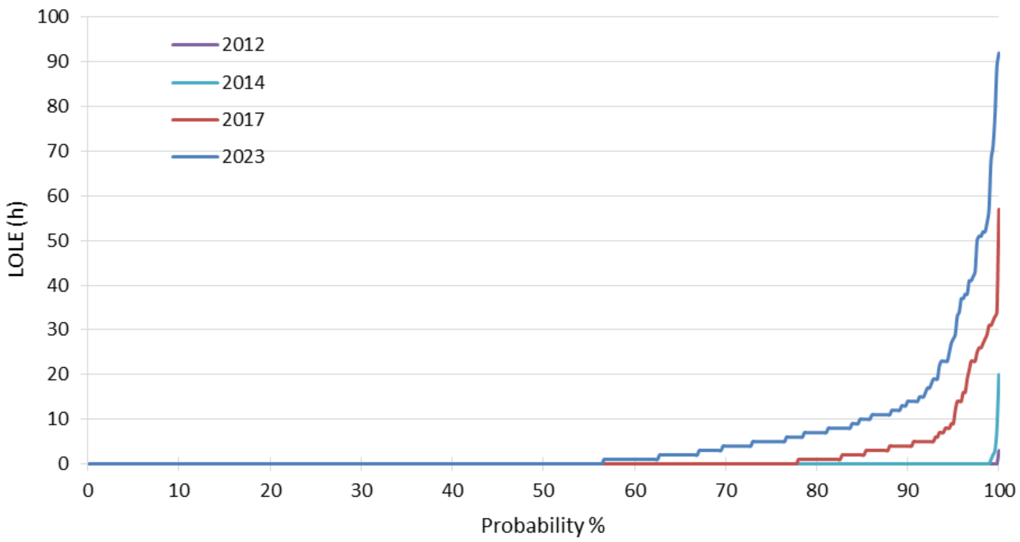

Figure 25: *The comparison of the duration curves of the loss-of-load expectancy index during the simulated years.*

The duration curves of the energy not served of the simulated years are presented in Figure 26. The figure shows increased amount of possible energy not served resulting from curtailment. This is in align with the duration curve of the LOLE index. As more curtailment hours is expected to occur, also more ENS will be observed.

The duration curve of the minimum remaining capacity (Figure 27) highlights the trend of the decreased adequacy level the best. Each curve consists of points that describe the lowest remaining capacity hour of each Monte Carlo case. A negative minimum remaining capacity means that curtailment would occur during an hour of the year at minimum.

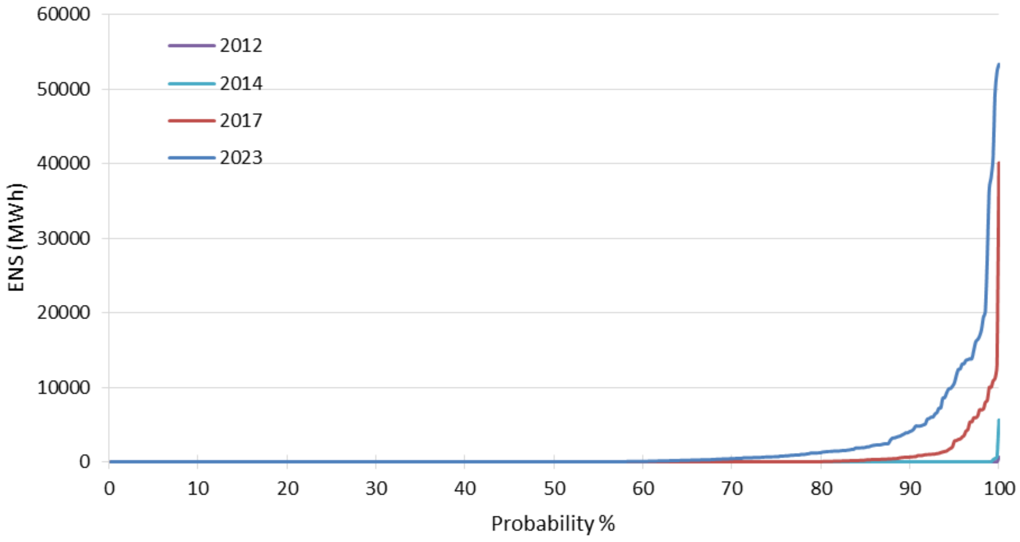

Figure 26: *The comparison of the duration curves of the energy not served index during the simulated years.*

In 2012, the minimum remaining capacity of Finland was below zero in one of 459 simulated Monte Carlo cases. In 2014, the minimum remaining capacity was negative in about one percent of the cases. However, curtailment occurred in 20 percent of the Monte Carlo cases in 2017 and in more than 40 percent of the cases in 2023.

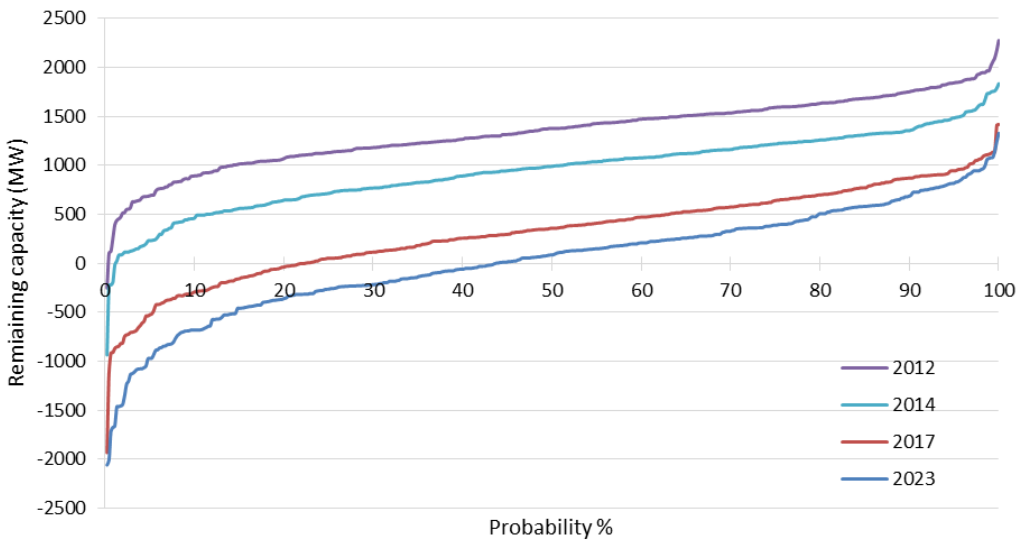

Figure 27: *The comparison of the duration curves of the minimum remaining capacity index during the simulated years.*

According to the results, the adequacy level of Finland has been decreasing since 2012 and continues decreasing until the last studied year 2023. Each of the three monitored indices verifies the same trend. A significant change on the development of the adequacy level of Finland can be seen after the year 2014. The adequacy level of 2023 is also significantly lower than in 2017.

In the recent years, there has only been a comparable study published which could be used to the comparison of the results of this study. VTT (2014) published a report on power adequacy in Finland in 2014 which, however, predicted significantly lower loss-of-load expectancies. According to the study, a LOLE under 0.01 h/year was expected in 2017–2021 assuming that Olkiluoto 3 is producing and 0.08 h/year if not. This thesis predicted a loss-of-load expectancy of 1.8 h/year for 2017 and 5.3 h/year for 2023.

The difference of the study results can be explained by different modeling assumptions for the available capacity in Finland. VTT's report was published two years ago and as stated in Section 3.1, there have been some major changes in the power market of Finland in the recent years. During the years 2013-2015, over 2000 MW of condensing power have been dismantled in Finland, which could alone explain the differences. Different methodology and assumptions in other input values might also affect the results. VTT used a frequency distribution method, whereas a chronological method was implemented in this study.

7.2.2 Case Study - Interconnector Analysis

Table 12 presents the best estimates for LOLE, ENS and the minimum remaining capacity of two scenarios, REF and PINT, in Finland. REF stands for the reference scenario and PINT for the scenario with the additional grid investment. The best estimates for LOLE and ENS include a confidence interval width with a 95 % certainty. The minimum remaining capacity is presented with the results of a simulated median year and a cold year. It corresponds to the 90th percentile of the sample in severity. The minimum remaining capacity corresponds to the most severe hourly situation during a year.

Table 12: *The LOLE, ENS and remaining capacity indices in the two scenarios. 2023 REF stands for 2023 case without any increase in interconnector capacity to Sweden. PINT scenario stands for a scenario where 800 MW increase to the interconnector capacity from Sweden was added.*

			Minimum remaining capacity (MW)	
Simulation	LOLE (h)	ENS (MWh)	Median year	Cold year once in 10 years
2023 REF	5.3 ± 1.1	1800 ± 550	90	-680
2023 PINT	0.70 ± 0.31	210 ± 110	750	30

The results show that a grid investment in the interconnector capacity of 800 MW from Sweden to Finland would increase the power adequacy level of Finland substantially. The potential investment would improve the adequacy level when looking at any of the adequacy indices. LOLE would decrease by a five-fold, ENS by a 9-fold and the minimum remaining capacity would increase during a median and a cold year by 660–710 MW. The estimated amount of LOLE in the PINT scenario relates to a level before the year 2017 which would satisfy the adequacy criteria in all of the reference countries in Europe.

The duration curves of the adequacy indices verify that the investment in the transmission capacity could solve the adequacy problems in most of the simulated cases in Finland in 2023. The comparison of the duration curves of the LOLE index (Figure 28) shows that both the expected probability of an occurring load loss and the total expected number of load loss hours would decrease. The blue curve of the PINT scenario shows that in less than 95 % of the cases a load loss of less than 3 h/years could be expected. The same value for the reference case would be 28 h/year.

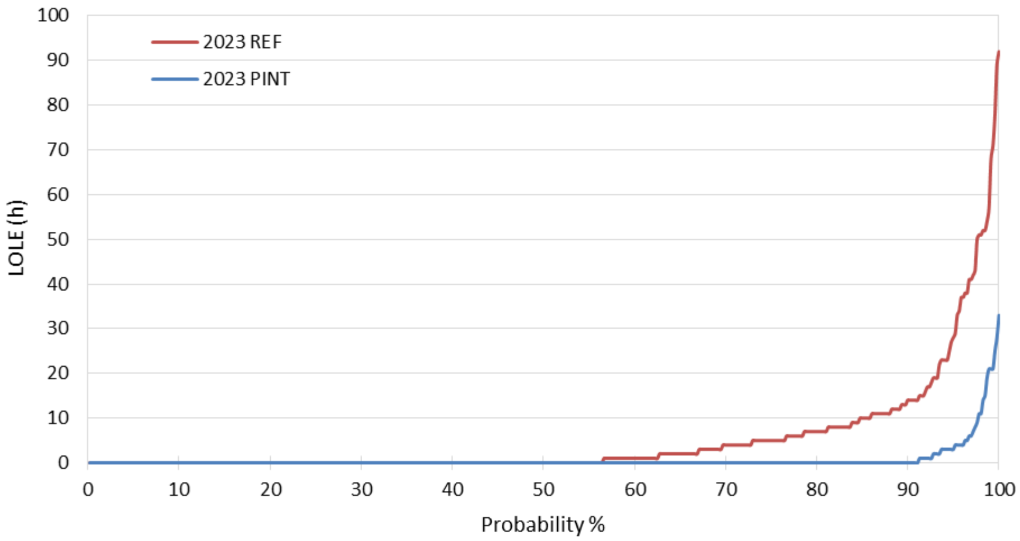

Figure 28: *The comparison of the duration curves of the loss-of-load expectancy index of the reference and PINT runs.*

Figure 29 shows the duration curve of the expected energy not served of two scenarios. According to the results, the increase in the interconnector capacity would decrease the amount of energy not served due to curtailment clearly in Finland. In the PINT scenario, over 300 MWh of ENS was expected in six percent of the cases. In the REF scenario, 32 % of the cases indicated higher ENS than 300 MWh per year.

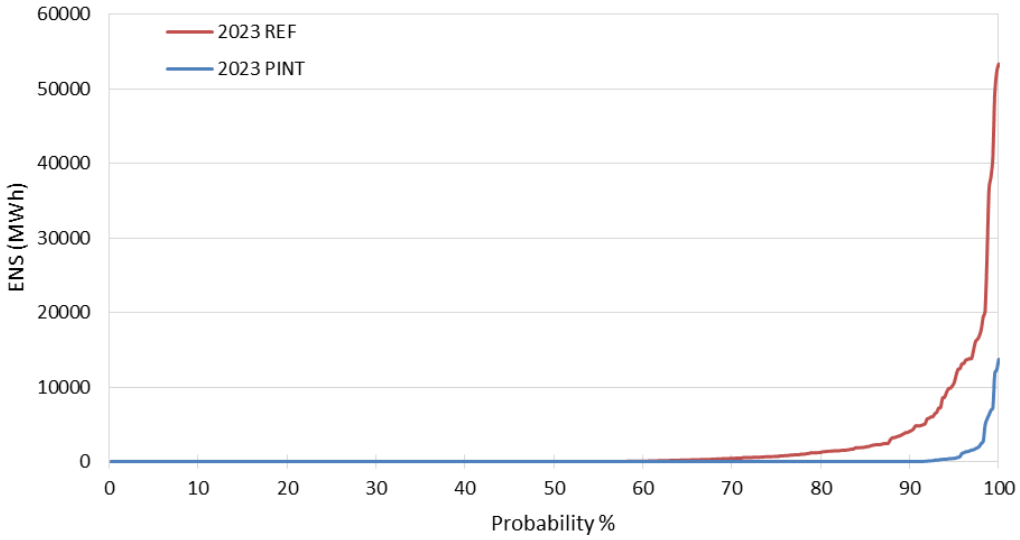

Figure 29: *The comparison of the duration curves of the energy not served index of the reference and PINT runs.*

Figure 30 shows the duration curve of the minimum remaining capacity of two scenarios. The blue PINT curve improves the minimum remaining capacity of each simulated case. The positive effect of the grid investment is higher when comparing the cases when the minimum remaining capacity was lower in the reference scenario. The positive contribution to the minimum remaining capacity of the investment is between 600–800 MW during the most severe 75 % of the cases. The maximum net positive effect of 800 MW was observed at the most severe 1 % of the cases.

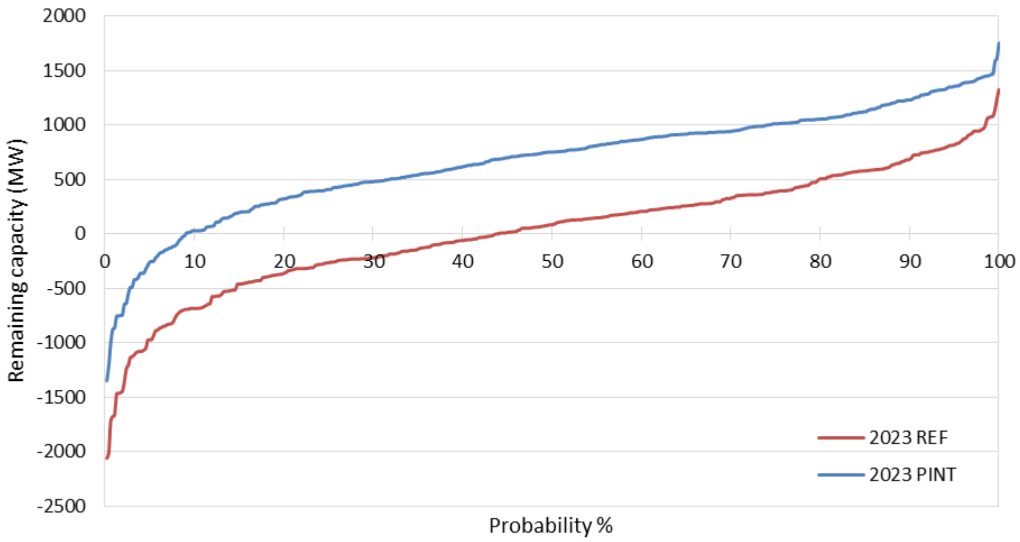

Figure 30: *The comparison of the duration curves of the minimum remaining capacity index of the reference and PINT runs.*

The case study of the effect of a grid investment on the power adequacy indices shows that 800 MW interconnector capacity increase would substantially increase the power adequacy level of Finland. The effect could be seen in all of the indices LOLE, ENS and remaining capacity. The duration curve of the minimum remaining capacity indicated that the grid investment improved the adequacy level in each of the simulated case. Also, it could be seen that the positive effect of the interconnector capacity increase was the largest in the most severe cases that were simulated.

7.3 Reliability Analysis on the Results

The scope of this thesis was limited to day-ahead markets which has a certain impact on the results and should be interpreted accordingly. It has an impact on both the available generation capacity and the assumed electricity demand which is explained on Section 2.1. For example, the capacity of the system service reserve is not included in this thesis since they are not bid to the day-ahead markets. An occurring load loss means in this study that the day-ahead market solution could not be established. This thesis, however, does not assess how it would be handled during the actual hour. The situation could be resolved by other market dynamics not represented in the model.

Also, the modeled results expect perfect foresight of the market. This means that all market players can perfectly estimate, for example the outages of units and weather conditions and act in a way that is optimal for the whole power system. This is an optimistic view of the market. Unexpected weather conditions and outages are prone to happen in the power system why the market players might not always be able to react optimally to the occurring situation.

Limitation on the created stochastic availability tool and the statistical input values for the generation of the unit outages and their duration should be considered. The statistical input values were rough estimations based on only two year period of forced outage data due to lack of appropriate data, why more data should be used for an appropriate calculation of the statistical input values. Also, the modeling of high impact low probability events were seen challenging with the tool.

The interpretation of the level of the results must take into account that all of the study years were simulated with some conservative base assumption. The most important factor, resulting from choice of the geographical perimeter, was the import capacity from Russia to Finland. The 1300 MW DC interconnector from Russia to Finland was not included in the study, which reduces the resulting adequacy level. However, the same geographical perimeter is used for all the case studies, which is why the study years can apparently be compared with each other.

Demand side response could potentially increase the adequacy level of Finland when becoming more common. However, demand side response was not modeled in the studies which is why the results do not take the possible growth of demand side response into account.

8 Discussion and Conclusions

This chapter discusses the main observations and findings about the proposed method and the conducted studies. The main conclusions are also presented.

8.1 Observations about the Proposed Method

The proposed method for assessing power adequacy is based on a chronological Monte Carlo Simulation method on an hourly resolution. The proposed method mostly aligns with previous adequacy assessment methodologies and their recommendations presented in Section 2.5. The method was created on the emphasis of firstly focusing on the most significant parameters affecting the current Finnish and secondly the Baltic Sea market area. Therefore, some differences can be seen in comparison with other studies in the field of area. In addition to implementing further development recommendations of previous studies, this thesis introduces a new method for the modeling of the power plant and interconnector outages.

The proposed method can be utilized to perform a stochastic analysis using a combination of weather dependent parameters and other random parameters. Wind power, hydro inflows, demand and CHP must run production related to district heating were modeled based on hourly, chronological, historical data which were system-widely harmonized. Some previous studies (Section 2.5.1) did not harmonize hydro inflows with the other weather dependent parameters due to the lack of data. Under the viewpoint that the studied power system involves the Scandinavian hydro-based power system, the harmonization of hydro inflows seemed as important for the correctness of the results as the harmonization of other weather dependent parameters.

In addition, the method introduces a new weather dependent parameter, CHP must run production, which was modeled to correlate with the temperature. CHP has a notable role in the current Finnish power system, which is why more detailed modeling of CHP was introduced. Under the hypothesis, CHP must run production related to district heating produces more electricity during colder temperatures than during milder temperatures, however, reaching maximum production at -5 °C. The effect of the temperature correlation can especially be seen during the winter season when there is a large variance in the temperature. Without the temperature correlation, an average CHP must run profile would indicate electricity generation that was too low during cold winter temperatures and too high during mild winter temperatures. According to Pöyry’s report (2015), the electricity generation of CHP can be seen to decrease 15 % during peak hour related to the increased need for heat. The decreasing effect was not taken into account in the temperature dependent CHP profiles.

In this thesis, a tool was created which generates stochastic availability profiles for power plants and interconnectors with a random sampling method. As far as the author knows, the tool is the first method in the field of study which models the outages of units chronologically from a frequency distribution function. This allows the tool to take into account that an occurring fault lasts for a certain period of time which variates stochastically according to a given average and standard deviation. The method can model outages with more variance compared with previously used deterministic modeling.

There was not much emphasis on the optimal number of historical weather years used in the previous studies. 51 historical weather years were used as input in this study. The number of years were chosen with the limitation of available data during the study, but 51 years is significantly more than what previous studies have been used. More years should represent the sample better and provide better results. The argument assumes that each historical weather year in 1962–2012 has an equal probability of occurring also in the future. However, the theory of global warming argues that the global temperature and other weather condition have been changing which would indicate that the recent, warmer weather conditions could occur more probably in the future than the colder weather conditions that occurred 50 years ago. Further research should be taken on this matter.

The proposed method was seen to model all the relevant, stochastical parameters in the studied power system. Future methodologies should also model solar as a weather dependent factor when solar power becomes a greater factor in the power systems of the Baltic Sea market area.

8.2 Sensitivity Analysis on the Simulation Parameters

Two sensitivity analyses were performed in this study concerning optimization parameters and the convergence of the results. On the contrary to the recommendations of previous studies, the sensitivity analysis on the optimization parameter indicated that the use of energy optimization did not notably affect the adequacy indices of Finland in the simulated power system. The results of each index LOLE, ENS and remaining capacity had only a small difference when using energy-optimization compared with capacity-only optimization. The capacity-only optimization could perform the analysis with a significantly lower simulation time, why it was used in the case studies. The case study in Section 7.1.1 showed that the amount of Monte Carlo simulations has a greater influence on the results than the used optimization setting.

The use of the energy modeling program settings should be re-evaluated depending on the characteristics of the studied power system and the used power market simulator. Units like demand side response, hydro power plants with small reservoir, electricity storage or other units with similar characteristics can only be modeled properly with energy optimization program settings that can take short term energy shortages into account.

As with all Monte Carlo simulations, the uncertainty of the results must be tolerated. The uncertainty can be improved by increasing the number of simulated Monte Carlo cases. The performed convergence study verified that a sample of 459 Monte Carlo simulation years is a representative sample of the simulated system with an acceptable confidence interval and the convergence criterion was met. The results are in align with the references of previous studies.

The certainty of the results can be analyzed with Byrne’s theory on the confidence intervals. Since the theory depends on the average and the variation of the simulated sample, the results of this study cannot be used to derive general conclusions. However, the conducted convergence study can be replicated to derive the confidence intervals for the results of other studies. The interpretation of a large enough sample of the set must be chosen accordingly with Byrne's theory, the results of the sample and the purpose of the study.

8.3 Applicability of the Method in the Case Studies

The conducted case studies showed that the proposed method seemed to produce reliable results when assessing the power adequacy of the Baltic Sea market area. The results of the case study 2012–2023 indicated that the adequacy level of Finland decreases during the studied time period. The result can be considered logical, since the amount of thermal generation capacity in Finland and its neighboring countries were also decreasing. The lowest loss-of-load expectancy was observed in Finland in 2023. The scope of this thesis was limited to day-ahead markets. Therefore, the results of this thesis do not indicate directly if load loss occurs during the actual hour. An occurring curtailment in this study means that the day-ahead market solution could not be established. The effect of the scope of this thesis on the results is discussed in Section 7.3.

The case study 2012–2023 showed that the adequacy indices of the proposed method could monitor the main changes between the simulated years. On the other hand, the available generation capacity of thermal power plants were expected to decrease due to dismantling both in Finland and in the neighboring countries in 2012–2023. On the other hand, the peak demand was estimated to slightly increase. Both trends should lead to a less adequate power system which could be seen with all of the adequacy indices accordingly in the study. This verifies that the proposed method works as intended.

The case study on the cross-border investment highlighted that the method can also be applied for grid investment analysis. According to the case study, 800 MW increase in the interconnector capacity between north of Sweden and Finland improves the power adequacy of Finland significantly. All three indices verified the same conclusion. An interconnector investment decreased the amount of case years when curtailment occurred, lowered the amount of curtailment hours per year, lowered the amount of energy not served during curtailment hours and increased the minimum remaining capacity of each simulated Monte Carlo case by 600–800 MW.

The method can be used as a tool for long-term system planning in various different applications. The method could be used to study the effect of peak load reserves, other interconnector investments or power plants on power adequacy. It should be highlighted that the proposed Capacity Margin run setting limits the analysis of units with short-term energy storage. For example, the analysis of demand side response or battery storage units would require run settings which take short-term energy constraints into account.

The effect of short-term energy storage units on power adequacy is recommended for further research. They were left as out of the scope of this thesis, but could possibly resolve many situations when curtailment occurs. Another interesting research topic for future is the duration of curtailment periods in comparison with the capability of short-term storage units. Short-term storage units that have a limited energy capacity can only resolve curtailment issues which last for a short period of time. The situation is similar to the temporary load-shifting.

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10 Appendices

Appendix A Algorithm for the Generation of the Duration of the Outage

```
Function DRAW_OUTAGE_DURATION(m, pSD, sChoice)
'******************************************************
   'The function draws the duration of the outage from a log-normal distribution function.
   'The algorithm is after: http://se.mathworks.com/help/stats/lognstat.html
    'A lognormal distribution with mean m and variance v has parameters mu and sigma which
   ' are the mean and standard deviation, respectively, of the associated normal distribution.

   'm = Statistical mean of the duration of the fault
   'pSD = Statistical standard deviation of the duration of the fault
   'sChoice = The chosen probability distribution
   'OUTPUT = Randomly drawn duration of the outage
'*******************************************************

Select Case UCase(sChoice)
    Case "LOG": 'Lognormal distribution
            v = pSD ^ 2
            mu = Application.WorksheetFunction.Ln((m ^ 2) / Sqr(v + m ^ 2))
            sigma = Sqr(Application.WorksheetFunction.Ln(v / (m ^ 2) + 1))
            result = WorksheetFunction.LogNorm_Inv(Rnd, mu, sigma)
End Select
DRAW_OUTAGE_DURATION = result
End Function
```